



UNIVERSITA' DEGLI STUDI DI PADOVA

**DIPARTIMENTO DI SCIENZE ECONOMICHE ED AZIENDALI
"M. FANNO"**

**CORSO DI LAUREA MAGISTRALE IN
ECONOMICS AND FINANCE**

TESI DI LAUREA

**"WHAT DRIVES THE GLOBAL FINANCIAL AND REAL CYCLES?
CLEARING UP THE LITERATURE MORASS"**

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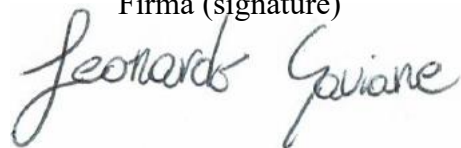
MATRICOLA N. 1209579

ANNO ACCADEMICO 2021 – 2022

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A handwritten signature in black ink, reading "Leonardo Saviane". The signature is written in a cursive style with a large, stylized initial 'L'.

Abstract

This thesis aims to study the importance of financial uncertainty, commodity prices and U.S. monetary policy on the global financial and economic cycles. Recent contributions have documented the role played by each of these shocks on the global economic cycle, and some of these shocks have also been identified as drivers of the global financial cycle. First, we estimate, with a dynamic factor framework that jointly models real commodity prices, a novel measure of commodity price index, that we call common commodity factor (CCF). The latter can be interpreted as the global demand for commodities associated with the business cycle. Second, through a VAR analysis and a recursive identification, we identify the impact and the contribution of the three shocks of interest on global financial and economic cycles. We prove the well-documented worldwide recessionary effect that the U.S. monetary policy and financial uncertainty shocks have, as well as the boom and bust that the CCF shock has. Finally, we conclude that uncertainty shocks are the main driver of the global financial and economic cycle, accounting for 45% of their volatilities.

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1 Introduction

This thesis aims to study the importance of uncertainty, commodity prices and the FED's monetary policy on the global financial and economic cycles. Recent contributions have documented the role played by each of these shocks on the global economic cycle, and some of these shocks have also been identified as drivers of the global financial cycle. But what is the relative importance of these shocks for the real and financial cycles at a world level?

This question is motivated by the following reasons. First, commodities prices faced unprecedented volatility in the last two decades, with simultaneous and alternating episodes of increasing and decreasing trends. The literature agrees that the rapid industrialization and urbanization in emerging economies of the early 2000s lead to higher global demand for raw commodities as manufacturing inputs; such events put unprecedented upward pressure on commodity prices. At the same time, commodities increasingly become part of portfolio allocation together with stock classes, drawing the attention of financial players (Creti et al. (2013) [34]). Hence, inflation stemming from commodities and their macroeconomic consequences becomes a central issue for the international economy and a subject of interest for policymakers and investors. Second, the strong financial integration in developed and emerging countries in the last decades hinted at the possibility of a common component that drives the movements in the worldwide financial market. The global financial cycle has recently been proposed not only as such common component but also as an empirical fact, possibly dampening central banks' ability to pursue domestic goals (Rey and Miranda-Agrippino (2015) [70]). So far, literature addresses US monetary policy and uncertainty about the changes in the global financial cycle. Though, they are not the only ones that play a crucial role. Hence, identifying the main driver(s) of such a cycle seems to be crucial to determine if and how to coordinate to dampen financial markets' fluctuations at a global level.

To answer our questions, we proceed as follows. First, as mentioned earlier, commodity prices are a leading indicator of expected inflation as they respond quickly to shocks in global economic activity and commodity-specific supply. Hence, to study the co-movement in commodity prices, we propose a novel measure of commodity price index via a dynamic factor model (DFM) à la Delle Chiaie (2022) [38]. Unlike the original work,

we use a broader and more complete database with real commodities return; moreover, our DFM uses a different block structure to model the idiosyncratic disturbances. The DFM allows us to disentangle price shifts driven by economic activity (demand) from the commodity-specific movements (supply). Therefore, we can decompose the prices into three parts: the common commodity factor (CCF), block-specific factors and an idiosyncratic disturbance. The former (CCF) is strongly linked to economic activity and captures the movements of demand for commodities associated with the business cycle. This point is further proven by the strong correlation with the CPB measure of world trade (0.846), an index that aggregates and summarizes worldwide industrial production and international trade. Block-specific factors capture price movements specific to the commodity belonging to that block and the idiosyncratic component, which is the part of the price that the factor model cannot explain.

In the second part of our investigation, we address the questions written above, namely, which is the main driver of the business and financial cycle between the US monetary policy, financial uncertainty and commodity prices shock. To answer these questions, we estimate a seven-variables VAR model, which includes our CCF, three US variables (i.e. CPI, industrial production and federal funds rate) and three state-of-the-art measures of global uncertainty, financial and real activity indices (i.e. the global financial uncertainty index (GFU) estimated by Caggiano & Castelnuovo (2021) [17], the global financial cycle (GFC) proposed by Miranda-Agrippino and Rey (2020) [62] and the world industrial production index (WIP) proposed by Baumeister and Hamilton (2019) [9]). Afterward, through a recursive (Cholesky) identification, we compute, first, the impulse response functions (IRFs) to analyze the dynamic consequences of an unanticipated shift in our variables of interest; then the forecast error variance decomposition (FEVD) to understand the relative contribution of each shock to other variables fluctuations. Our VAR analysis points out that GFU shocks have a negative impact on both the global financial cycle and global output, with a median contribution to the global financial and activity cycle, respectively, of 47.16% and 27.52%. Interestingly, CCF shocks have a short-run positive effect on WIP and GFC, in line with the findings of Kang (2020) and Killian & Park (2009) [57] [54]; i.e. unanticipated shifts in global demand for inputs associated with business cycle increase economic activity and stock returns; because the stimulating effects dominate in the short-run and financial and business cycle thrive despite the price increase. On the other hand, after one year, the global financial and business cycle

decline; a possible explanation is provided by Reinhart (2009) [69], suggesting that, in periods of wealth, the capitals flow in emerging markets, increasing commodity and asset prices but, ultimately, exacerbating structural weaknesses in the country. The federal funds rate shocks lead negative response in GFC but positive in WIP, contrary to what common DGSE models suggest.

To solve the puzzle of monetary policy shocks, the findings of Hoesch et al. (2020) [52] come in handy. They claim that researchers sometimes can achieve wrong results when estimating monetary policy shock. They explain that these deceiving results are due to an *information channel* that appears when FED communicates its policy. Agents believe that the FED has an *information advantage* with respect to the public and has deeper knowledge about the status of the economy. When the FED raises interest rates to manage expectations about the over-heating of the economy and future inflation, agents learn about the status of the economy and fulfill that expectation. As a consequence of a monetary policy shock, an increase in inflation and production is achieved, conversely to FED's intentions. Hoesch et al. (2020) [52] and Lunsford (2020) [60], found evidence of a structural break on August 2003, that translates into strong weakening of the *information channel*. They attributed the disappearance of the information channel to a change in FED's communication strategy, namely the adoption of policy-inclination forward guidance and overall transparency. Moreover, since the mid-2000s, aside from the weakened *information channel*, FED has lost its short-run *information advantage* over market players on the status of the economy.

In the third part of our investigation, we take into consideration the findings of Hoesch et al. (2020) [52], and we re-run the VAR analysis over a smaller sample, namely from August 2003 to April 2019. Then we compare the IRFs and FEVDs of the sub-sample with the full sample. A sub-sample analysis is further motivated by Erdem (2016) [41], whereas BRIC countries entered a period of strong economic growth since mid-2003 putting pressure on global commodity demand. The findings can be summarized as follow: *i*) After August 2003 the information channel weakens, and a contractionary monetary policy shock leads to a more severe reduction of US and world economic and financial activity in the short run. The contribution of the US monetary policy shocks to the GFC and WIP doubled in the sub-sample (11.21% and 12.67%, respectively). The IRFs confirm the findings of Hoesch (2020) [52] mentioned earlier. Moreover, as in Miranda-Agrippino and

Rey (2020) [63], we unveiled the powerful recessionary effect that US monetary policy has cross-border that is transmitted through the global financial cycle. *ii*) After August 2003 an Uncertainty shock plays a much smaller role in explaining the interest rates adopted by the FED but a more relevant role in output variables (40%). This result is in line with Caggiano et al. (2017) [18] where uncertainty contributes less to fluctuations of the interest rates in the presence of the zero lower bound but has a stronger effect on output. *iii*) Financial uncertainty shock has a negative impact on the commodity factor and contributes to a large fraction of its volatility (28% at the 2-year horizon). *iv*) Commodity factor shocks lead to an increase in the world economic and financial activity in the short run, but a recession after. The contribution to GFC and WIP is higher in the short-sample (11.74% and 5.69% respectively) than in the full sample (4.4% and 1.79%). We attribute the higher contribution of the shocks to a higher level of global trade in the sub-sample. *v*) Commodity factor shock increases CPI and decreases (mildly) US industrial production and interest rates over time. Moreover, the commodity factor shock seems to explain a big part of the variability in the Federal funds rate (20.24% of the variability at the 1-year horizon), especially after August 2003. *vi*) Uncertainty shocks appear to be the main driver of business and financial activity on all years' horizons. At one year, the CCF shocks contribute more than monetary policy shocks to fluctuations in GFC (14% and 6.6% respectively); however, they contribute equally in a 2-years horizon. CCF shocks are far less relevant than federal funds rate shocks to fluctuations in WIP (5.69% and 12.67% at two years horizon respectively). This confirms the finding of Caggiano and Castelnuovo (2021) [17], that addresses uncertainty as the main driver of the global financial cycle and real activity.

The rest of this thesis proceeds as follows. In subsection 1.1, we review the related literature and deepen some topics: global financial cycle, financial uncertainty and information channel. In section 2, we build the common commodity factor and perform some case studies on commodity-specific events. In section 3, we discuss the econometric framework adopted in the VAR analysis (SVAR, IRFs and FEVD) and implement it in our samples. In section 4, we draw the conclusions.

1.1 Related literature

Our thesis has been inspired by the literature about global financial cycle (GFC) (Rey (2015) [70], Miranda-Agrippino (2015) [64], Davis et al. (2019) [36] Miranda & Rey (2020), [62], Miranda & Rey (2021) [61]). As said in the introduction, such GFC has been recently proposed as a common component that explains a large part of the variation in assets and has strong implications for worldwide monetary policy transmission. Habib et al. (2018)[49] further explore this topic and found evidence of co-movements between asset prices and flows of capital among different countries, and such co-movement is stronger during the 2007-09 recession. Interestingly, also global stock market volatility and commodity prices have seen unprecedented common fluctuations over the last two decades, notably during the global financial crisis. Recently, the literature has proposed links between commodity prices, finance and real activity. For example, Creti (2013) [34] argued that the link between commodity price and stock market volatility strengthened during the 2007-09 crisis; moreover, many commodity prices are characterized by a speculation phenomenon. Ertem (2016) [41], argues that the strong co-movement between commodity prices in the early-2000s is mainly driven by business cycles along with the financialization of commodities. Killian and Park (2009) [57], found that global oil supply and demand shocks contribute to up to 22% of the volatility in US real stock returns. Kang et al. (2016) [55] found that US oil output has a beneficial impact on the US stock market, and they claim that both supply and demand oil shocks are essential in explaining US real stock returns. Kang (2019) [54] argue that the stock exchange volatility and commodity price shocks are likely to interact and influence one another's economy. Stock return volatility is positively associated with gold futures prices and adversely related to oil price futures, according to Chiarella et al. (2016) [30]. Fernández et al. (2017) [44], changes in commodity prices and the global interest rate account for almost a third of the variance in output, consumption, and investment in developing nations. Erten (2013) [42] proved the existence of long cycles (super-cycles) in commodities prices, periods of sustained commodity prices and demand increase in response to emerging market growth. Delle Chiaie et al. (2017) [37] puts the foundations of our thesis, proving the existence of a common factor among the risky commodities; such component is strictly linked to the business cycle and global demand for commodities. Reinhart (2016) [68] and Reinhart (2009) [69] studied the implications of cash inflows, commodities' super-cycle and default risk of an emerging market, finding that emerging markets are more vulnerable to crisis

and that capital flow bonanza ends in parallel with the increase of worldwide sovereign debt default risk. Moreover, all the major spikes in sovereign defaults came on the heels of surges in capital inflows, when followed by an increase in inflows and commodity prices. Ultimately such a link between cash flow and commodities arise also in the findings of Davis et al. (2019) [36], which we will discuss later. The effect of oil supply, demand and inventory shocks on the economy have been studied in a wide range of literature (Caldara et al. (2019) [21], Baumeister & Hamilton (2019) [9], Baumeister & Kilian (2016) [10] Killin (2009) [56]), the most recent finding proved that supply shocks are far more relevant in determining oil price changes and lead to negative response of industrial production, while the response of output is positive for demand shocks. Though, the impact of the common component of commodities on global financial and real cycle is still an object of studies. On the other hand, recently, the literature hails uncertainty as one of the main drivers of the business and financial cycle, though uncertainty measures are still at their early stages, as their studies started recently. For instance, Bloom (2009) [15] to understand macroeconomic effects of uncertainty focused on the VIX measure, using stock market volatility as a proxy for uncertainty, finding that a shock in the variable depresses economic activity in the short-run and bounce in the long run. More recently have been built uncertainty indices; for example, Baker et al. (2016) [5] built an economic policy uncertainty index which has been build counting how many times a set of specific words appears in the newspaper; for example, Jurado et al. (2015) [53] create a measure of US macroeconomic uncertainty through a dynamic factor model framework and show that the behavior of their measure of uncertainty differs from that of others proxies in the literature. Caggiano & Castelnuovo (2021) [17] similarly created through a dynamic hierarchical factor model a global financial uncertainty index (GFU), proving financial uncertainty has a significant impact on GFC and WIP. Angelini, Bacchiocchi, Caggiano, and Fanelli (2019) [2] and Ludvigson et Al. (2021) [59] both agree that financial and macroeconomic uncertainty are both exogenous and relevant drivers of the business cycle. In Caggiano et al. (2017) [19] they found that monetary policy at the zero lower bound does not respond to uncertainty shocks as in normal times and has more significant recessionary effects. Hoesch et al. (2020) [52], and Miranda-Agrippino et al. (2021) [65] study the information asymmetries between the public and the central bank that can give rise to an *information channel* for monetary policy actions. In the following paragraphs, we are going to review the most relevant literature briefly to understand our thesis.

Miranda-Agrippino & Rey (2020) [63] In Rey (2015) [70] They explore the large evolution of the financial integration our world is facing. In the last decades, both developed and emerging countries have increasingly opened their borders to financial flows. They noted strong commonalities between risky asset prices and capital flows¹ (net and gross flows), leverage and financial aggregates and across regions. Moreover, other researchers suggested the VIX² as a determinant of inflows and outflows of capitals. Therefore, when VIX spikes, capital flows decline, credit growth decreases, and vice versa in periods of low volatility. These strong co-movements are synchronized with world market risk aversion and uncertainty fluctuations and can be translated as the global financial cycle (GFC henceforth). Such GFC has been built by using a dynamic factor model and a large dataset of more than eight hundred risky asset price series since these assets follow the movements of the GFC. The factor is shown in figure 1. Since the strong relationship that assets prices have with the uncertainty, it is highly correlated with VIX, and it accounts for a quarter of the fluctuations in risky assets prices.

In the paper Miranda-Agrippino & Rey (2020) [62] they explore empirically the international transmission of USA monetary policy that occurs through financial intermediation and global asset prices. Their study stems from the idea that US monetary policy may affect the cost of funding and alter the worldwide pricing of the dollar assets through a direct discount rate channel or by changing the type of marginal investors in international asset markets. Moreover, the monetary condition of the US can be transmitted through cross-border capital flows³ through the internal pricing of liquidity of global banks, which may influence the credit outside America. Through a proxy-SVAR analysis, they proved their thesis and found evidence of significant financial spillovers from US monetary policy to the rest of the globe. When the Federal Reserve increases interest rates, domestic demand and prices fall. More signs of domestic financial transmission lead to an increase in corporate spreads, a credit contraction, and a dramatic drop in asset prices. Nevertheless, they establish large alterations in the Global Financial Cycle alongside domestic effects. Risky asset values decrease dramatically when summed up by a single global factor. This

¹For example Equity, FDI, Debt and Credit flows

²It is a measure of the implied volatility of S&P 500 index options.

³Since the global financial factor does not exist only in risky assets prices, Davis et al. (2019)'s [36] built a latent factor model that jointly analyzes global drivers of gross flows (outflows plus inflows) and net flows (outflows minus inflows) across countries. The first factor they extracted (gross flows factor) appears to be strongly correlated with the GFC of Miranda-Agrippino Rey, and they call itself the Global financial Factor. While the second factor (Net-Flow factor) closely tracks the movements of oil and gas prices. Both factors have large explanatory power for gross and net flows. Moreover, the GFC (Davis et Al.) largely explains the variability of net flows and commodity factor.

is accompanied by a deleveraging of global banks in both the United States and Europe and a rise in global asset markets' collective risk aversion. Global credit contract availability declines, and international credit flows slow significantly, especially in the banking industry. International corporate bond spreads increase sharply as a result of the monetary policy shock. Moreover, interest rates abroad fall as a result of deteriorating economic conditions. Floating exchange rate regimes are not successful in providing a protective shield against US monetary policy shocks, as the GFC affects every country equally in the same way. This is the result of the dollar being the dominant currency in international financial transactions and the interconnection of global financial intermediaries. These facts debunk the trilemma⁴ of Mundell (1963) [66] to a dilemma or irreconcilable duo, as monetary conditions are transmitted from the main financial centre to the rest of the world through gross credit flows and leverage, and of the exchange rate regime does not insulate a country from the external shocks. As a result, regardless of the exchange rate regime, independent monetary policies are only feasible if and only if the capital account is regulated, directly or indirectly. Gross and credit flows must be monitored carefully as they are relevant for financial stability. By looking at cross-border gross flow position, currency and maturity miss-match can be tracked. The latter is important as they have been proven to be indicators of financial instability. Net flows do matter, as they are important for sustainability issues (Gourinchas & Rey (2007) [48]). To deal with GFC, Rey & Miranda-Agrippino (2015) [64] suggests the following: *a*) Capital controls. To insulate the country from foreign financial shocks, permanent or cyclical capital controls might be considered. On the inflow or outflow side, permanent capital controls can be implemented on a subset of assets. Instead, temporary or cyclical capital controls might be employed to limit portfolio debt and credit flows during the GFC's boom period. Capital controls might be paired with macroprudential instruments, which help to reduce the relationship between domestic financial conditions and the Great Recession. For example, if the central bank limits financial firms' incentives to borrow from other nations, the GFC's transmission channel would be severely harmed. In summary, a country may protect itself against foreign financial shocks by addressing the dilemma's two components: capital account openness and domestic monetary policy. *b*) The internalization of the global spillovers of the centre's monetary policy. The consequences of central bank policy in major nations on other countries are currently not understood. Central bankers in systemically signif-

⁴For a country it is not possible to have an open capital account, fixed exchange rate regime and independent monetary policy all at the same time

ificant nations should pay more attention to their collective policy stance and its global ramifications. "A small group of systemically significant central banks meeting frequently under the umbrella of the BIS Committee on the Global Financial System" would be one feasible approach to put this into practice. This group would debate and evaluate the effects of their policies on global liquidity, leverage, and exposures and the propriety of their combined money and credit policies in terms of global pricing, production, and financial stability. *c)* Muting the transmission channel of the global cycle by taking cyclical measures (macroprudential measures) to limit excessive credit growth. The concept is to employ national policy to cyclically regulate credit growth and leverage. Credit expansion and leverage, in particular, should be restricted during upswings in the cycle and enhanced when a downturn occurs. As a result, monitoring banks' trading strategy and lending criteria during periods of credit growth might be beneficial. Basel III, for example, includes valuable indicators like the Liquidity Coverage Ratio and the Net Stable Funding Ratio for assessing liquidity risk. Aside from the equipment, intervention time is critical, and waiting too long can be disastrous. As a result, setting automated rules that activate when certain indicators of a bank's financial stability reach a certain level is possible. Finally, stress testing may be used to measure the impact of changing asset prices on the balance sheet and, as a result, on domestic financial circumstances. *d)* Muting the transmission channel structurally by dampening the amplification capacity of financial intermediaries: tougher limits on leverage. It entails intervening in the GFC's transmission channel "by establishing tougher leverage restrictions for all financial intermediaries". Banks and other financial intermediaries' financial amplification mechanisms would be limited due to such a regulation. By limiting a bank's capacity to leverage up, the pro-cyclicality of their balance sheets would be reduced, and loan growth would stay stable. As a result, the GFC breaking in across national borders would be less concerning.

Caggiano, Castelnovo. (2021) [17] Their paper proposes a novel uncertainty measure, the global financial uncertainty (GFU). Their measure has been built through a dynamic hierarchical factor model, using a large dataset of monthly realized volatilities of the exchange rate, stock market returns and government bond yields. The factor is modeled to take into consideration regional dynamics. The GFU comoves with measures of financial uncertainty such as the VIX and Ludvigson, Ma and Ng (2021) [59] displaying a high correlation. The GFU correlates with the measures of macroeconomic uncertainty as well, especially during great recession, although the pairwise correlation is lower than

one. However, strikingly, GFU has a poor correlation with the most relevant uncertainty indices, eg. The Economic policy index by Baker, Blom and Davis (2016) [5], world uncertainty index by Ahir, Bloom, Furceri (2022) [1] and geopolitical risk measure by Caldara and Iacoviello (2022) [22]. This poor correlation between the other measure can be interpreted as the GFU carrying new information about uncertainty. Most interesting, they run a VAR analysis and found that an uncertainty shock has a large negative impact on the global financial and real cycle, with a median contribution of 30% and 9%, respectively. These results concern us because they proved that uncertainty shocks, primarily "financial", are the main drivers of the global financial cycle.

Reinhart (2009) [69] In their paper, they study the effect of capital flow bonanzas into emerging markets. To do so, they used a large cross-country dataset of reserves (minus current account), inflation and real GDP and exchange rate, and sorted the country by income level, and through a threshold rule, they selected countries that had capital flow bonanzas. First, they noted that when interest rates decrease or growth slows in advanced economies, Investors look for higher yield and profits in emerging markets, confirming the findings of Calvo et al. (1993) [25]. As capital flows in, the exchange rate appreciates, asset prices increase, and commodities boom. The capital inflows, therefore, improve fiscal indicators as well as consumption. On the other hand, weaknesses in the domestic banking sector are exacerbated, and a country, to avoid currency appreciation, has to sell its reserves. Second, policymaker tends to treat these periods of capital flow bonanzas as permanent rather than temporary, most of the episodes studied in Reinhart (2016) ends up with a *sudden stop* à la Calvo (2004, 2006) [23][24] or with a current account reversal à la Milesi-Ferretti and Razin (2000) [45]. The former, and more likely, happens when capital no longer flows into an emerging market and the nation can no longer support an excess of spending over income. In their study, capital inflows bonanza periods are associated with a higher probability of currency, banking and inflation crisis in the low-income economy; in addition, they systematically precede a sovereign default episode, this helped by the fiscal policy that plays a destabilizing role. During the run-up of the bonanza, real GDP and equity prices increase to become lower as the capital flow away. Similarly, as commodity prices rise, investors seek profits somewhere else.

Hoesch et Al. (2020) [52] According to Campbell et al. (2012, 2017) [27][26], survey-based estimates of an expected production growth surge in reaction to unexpected rises in

interest rates, whereas those of inflation drop. Which is the opposite of popular new Keynesian beliefs. Hoesch et Al. (2020) [52] explain this controversy through the *information channel*. After an unanticipated monetary policy shock, agents assume that FED has more insights about the economy (*information advantage*) and, therefore, learns about macroeconomic fundamentals as well as the path that the federal reserve wants to pursue with the monetary policy. Therefore agents update their beliefs if the status of the economy, communicated through interest rates, differs from their expectations. For example, suppose a contractory monetary policy is an endogenous response to a future condition of the economy, and agents think that it is more favorable than market forecasts. In that case, they may foresight future production and inflation to rise, and their expectations will be updated appropriately. Under these circumstances, the results can be deceiving. The *information advantage* as well as the *information channel* weakened in early-mid-2000s. They argued that the main reason why the *information channel* disappeared is due to a transformation of the FED's communication strategy and overall transparency. FED does it by including time-dependent forward guidance in its post-meeting statement. They find evidence of a structural break in august 2003, which confirms the finding of Lunsford (2020) [60]. The latter also showed that the private sector's responses to Federal Open Market Committee (FOMC) monetary policy announcements are strongly shaped by forward guidance; moreover, forward guidance delivers higher information than communicating policy inclination. Hoesch et Al. (2020) [52] conclude that the FED has lost its short-run information advantage over market players on the status of the economy. Furthermore, the FED can no longer anticipate market surprises, and private expectations of macroeconomic conditions are less susceptible to interest rate shocks. Ultimately, They found that IRFs for a monetary policy shock deliver correct results only if the monetary policy instrument is information-robust before august 2003, which means that the instrument does not carry any information about the endogenous intent of the FED. IRFs computed with a proxy-SVAR after august 2003 deliver theoretically correct answers. Even though we are not going to use a proxy-SVAR, we are concerned about this because we will test our impulse responses with our means; therefore, changing the sub-sample delivers different results.

Wu and Xia (2016) [75] Their paper argues that the Effective federal funds rate (EFFR) conveys information about the FED's reaction to changes in the macroeconomic environment. Unfortunately, though, since 2009, the EFFR ceased to play this role, as it

reached the zero lower bound (ZLB) and FED relies on unconventional monetary policy (quantitative easing (QE) and forward guidance) to influence the economy. To assess the impact of these policies at ZLB and summarize their effect, Wu & Xia (2016) developed through the shadow-rate term structure model (SRTSM) a novel measure of interest rate, namely, *shadow rate*. The latter can be considered the negative value that the interest rate would achieve when conventional and unconventional monetary policies are considered. First, they replace the value of EFFR after 2009 with the shadow rate, achieving a new measure of monetary policy. Second, they confirm that the shadow rate can be used as a substitute for EFFR, as their policy rate exhibits similar dynamic relations to crucial macroeconomic variables before and after the Great Recession, which confirms that the shadow rate captures meaningful information missing from the EFFR when it is at the ZLB. Ultimately, through a VAR analysis, they compare the impact that shadow rate has had since 2009, and they found that it delivers qualitatively similar results to the full sample. The result is reported in figure 3.

2 The common commodity factor

2.1 Empirical analysis

2.1.1 Dataset

Our dataset is comprehensive of a wide range of real spot price series. We extend the number of internationally traded commodities that were present in Della Chiaie et al. (2017) [37] from 52 to 68, each belonging to a different category: fuel, beverages, food, agricultural raw materials, metals, fertilizer, and precious metals commodities. The data have been downloaded from the IMF primary commodity price database, which comprehends the most relevant commodities in terms of trade value. The commodity prices series were originally monthly period average and were expressed as current US dollars; then, they were deflated by CPIAUCSL to express real prices. For the purposes of the estimation in the next section, we require our data to be covariance stationary; therefore, we took the log difference of all price series. In addition, we further transform the data such that the sample mean is zero and has a unitary variance. The sample I use to extract the factor begins on February 1990⁵ and it ends on November 2021⁶.

In Table 2 we report the list of price series used to build the factor along with the relative weights. The weights are those reported in the technical documentation of the IMF Primary Commodity Price Index. Global import weights are computed over three years (2014-2016) on selected commodities in the following way:

$$\Omega_t^k = \frac{\omega_t^k}{\sum_{k=1}^{68} \omega_t^k} \quad (1)$$

Where ω_t^k are the global import at time t for commodity k . The resulting Ω_t^k that is the weight used to compute the commodity price index; it can be considered as the share of worldwide commodity k imports over all commodities imports. An important feature to notice is the presence of a block structure in the dataset. In Table 1 we exploit different levels of aggregation of the indices. The Global commodity index is the weighted average of the commodities price series. It can be divided into two main block indices, namely energy and non-energy. The non-energy block is characterized by three sub-blocks: fertilizers, industrial input and food & beverages. Food & beverages can be broken down into two more groups: food and beverage. Similarly, industrial inputs can be broken down into

⁵First observation is lost because log-difference

⁶Some price series were not available since January 1992 but, as suggested in Banbura and Modugno (2014) [7], maximum likelihood estimates can be adopted to deal with missing data.

agricultural raw materials, metals and precious metals. The Energy group can also be divided into three sub-categories: crude oil, natural gas and coal.

It is worth noticing in Table 1 that even though non-fuel indices represent 59.1% of the global index with 59 price series, the fuel index represents the 40.9% of the global index with nine commodities. Our weights are different⁷ from the ones used in the paper Della Chiaie et al. (2017) [37]. In sub-section 2.2.1 we compute - along with the factor- the IMF commodity index with our weights.

The IMF commodity database has been updated during the last years, so the number of blocks has changed; for example, some series, such as natural gas, coal and fertilizers, have been added. To estimate the common factors, we require a block with a strong local correlation. Precious metals commodities present a strong degree of correlation within the block and also with other commodities. Starting from table 3, we selected gold as a representative commodity of the precious metal block. As we can see, it is correlated with many factors from a different group and, interestingly, presents a high degree of correlation with oil⁸. One possible explanation is that people tend to save and invest in hedge risk commodities in a period of increasing uncertainty and uncontrolled commodity price increase, e.g. Pre-Global financial crisis. In Table 4, we can see that gold is -not surprisingly- strongly correlated with other precious metals. Therefore, investors who hedge risk and purchase safe heaven commodities may want to lower their exposure to gold risk and diversify their portfolios with other commodities. This can be an explanation of the co-movement of the hedge risk assets commodity prices⁹. Summing up, we add four new sub-blocks: fertilizers, precious metals, coal and natural gas.

2.1.2 Model and estimation

We follow the footsteps of Della Chiaie et al. (2017) [37] and adopt an approximated factor model, which is an efficient method to represent the dynamic co-variation among a set of random variables for large cross-sections. Each series in the n-dimensional vector of commodity return is covariance stationary with mean zero $y_{it} = (y_{1t}, \dots, y_{nt})'$, and has

⁷Weights used in the paper of Della Chiaie et al. (2017) [37] are computed on the 2001-2003 period, which attributes more weight to energy commodities (about 60% to fuel commodities and 40% to non-fuel commodities), while I use the 2014-2016 weights which consider non-energy more relevant (see Table 1).

⁸In line with the finding of Fernandez et al. (2020) [43].

⁹This idea has been further developed from Peiffer & Podstawski (2018)[67], where they construct a proxy for uncertainty shock exploiting gold price changes around uncertainty episodes.

a factor representation, the model can be written as follow:

$$y_{it} = \lambda_i f_t + v_{it} \quad (2)$$

Where a series y_{it} can be expressed as the sum of two unobserved components: the global, or common, component f_t and an idiosyncratic component e_{it} . The global component $f_t = (f_{1t}, \dots, f_{rt})'$ is an r -dimensional vector of global pervasive factors which affect all commodities, and it captures the bulk of the cross-sectional component. The idiosyncratic component e_{it} reflects specific shocks of the factor or measurement error, which is assumed to be non-pervasive and weakly correlated across commodities. At all leads and lags, the idiosyncratic component e_{it} and common factors f_t are uncorrelated. The vector of factor loadings is $\lambda_i = (\lambda_{i1}, \dots, \lambda_{ir})'$, where each item measures the impact of the global factors to the commodity i .

The common factor are modelled following an autoregressive process of finite order p :

$$A(L)f_t = \nu_t \quad (3)$$

$$A(L) = I - A_1L - \dots - A_pL^p \quad (4)$$

where (4) is an $(r \times r)$ filter of finite length p with roots outside the unit circle, and ν is a Gaussian white noise, $\nu_t \sim i.i.d.N(0, I_r)$. The block factor structure serves to model parsimoniously the local correlation among idiosyncratic components. That means e_{it} can be decomposed into factors which are specific to blocks, sub-block or groups of commodities¹⁰ and a pure idiosyncratic component; hence

$$v_{it} = \sum_{i=1}^K \psi_{ij} z_{jt} + \epsilon_{it} \quad (5)$$

$$\psi_{ij} = \begin{cases} \neq 0 & \text{if } i \in j; \\ 0 & \text{else} \end{cases} \quad (6)$$

where z_{jt} is the block j at time t , ψ_{ij} is the block j loading and it will assume value 0 if commodity i does not belong to block j . The pure idiosyncratic component ϵ_{it} as well as the z_{jt} follow an autoregressive process of finite order:

¹⁰In our case the blocks taken into consideration follow Table 1, we are going to talk about this in sub-section 2.1.4

$$z_{jt} = \alpha_j z_{jt-1} + \eta_{jt} \text{ with } \eta_{jt} \sim i.i.d.N(0, 1) \quad (7)$$

$$\epsilon_{it} = \beta_j \epsilon_{it-1} + \varepsilon_{it} \text{ with } \varepsilon_{it} \sim i.i.d.N(0, \sigma_i^2) \quad (8)$$

The assumption behind these equations is that commodities belonging to the same market are correlated because of common -or complementary - technology shocks, while commodity-specific shocks cannot affect other markets' commodities; hence, block factors are not correlated. This is in line with the assumption of Baumeister & Killian (2014). [10], where they conclude that the pass-through of oil price shocks to other commodities markets is narrow. Factor model estimation adopts a quasi-maximum likelihood for the approximate model as in Doz, Giannone, Reichlin (2012) [39].

2.1.3 Maximum likelihood estimation

In this subsection, we are going to talk briefly about the quasi-maximum likelihood estimation we used in our model, carried out using the Expectation-Maximization (EM) algorithm as proposed in Doz, Giannone, Reichlin (2012) [39]. Our purpose is not to show to explain the econometric framework deeply but to give a general idea of the properties.

A large literature consider the principal components as the solution of the computational problem, since even if cross-sectional dimension n is larger than sample T it can be easily computed and, most importantly, can deliver consistent results for any path of n and T , especially if the cross-section dimension is large, Forni et al. (2000) [47]. Although, maximum likelihood methods are more appealing, as they can lead to efficiency in gains and, especially, allow to implement restrictions derived from the economic theory in the model. In Doz, Giannone, Reichlin (2012) [39] they estimate a model with orthogonal idiosyncratic elements, *exact factor model*, and derive the n, T rate of convergence for the maximum likelihood estimates of the common factors. Then they treat the *exact factor model* as a *misspecified approximating factor model*, and analyze the properties for $T, n \rightarrow \infty$. The properties are checked on the maximum likelihood estimator of the factor when the true probabilistic model is approximated by a more restricted model, which is under misspecification. In order to find r common factors given the observations X , we need to relax the *exact factor model* with some assumptions, such that it becomes "Approximate".

1. n has to be sufficiently large, such that $\lambda\lambda'/n$ has full rank r . This assumption is required to keep the factor pervasive as the number of series in the data set increase.
2. Cross-correlation of idiosyncratic components is limited. With respect to exact factor model which includes the case in which they are mutually orthogonal, Approximate factor model follow a more generic structure.
3. Given: M as any positive square matrix, a stochastic process $\{X_{n,T}; T \in Z, n \in Z\}$, $E[e_{it}e_{jt}] = \tau_{0,ij}$, assuming that the normalization constraint $E[f_t f_t'] = I_r$ can be adopted; there exists a positive constant M such that for all $i, j \in N$ and for all $T \in Z$:

- i. $E(\sqrt{T}(\frac{1}{T} \sum_{t=1}^T e_{it}e_{jt} - \tau_{0,ij}))^2 < M$

- ii. $E\|\frac{1}{\sqrt{T}} \sum_{t=1}^T f_t e_{jt}\|^2 < M$

- iii. $E\|\sqrt{T}(\frac{1}{T} \sum_{t=1}^T f_t f_t' - I_r)\|^2 < M$

this assumption requires that the entries of the sample covariance matrix of the common factors and the idiosyncratic components are \sqrt{T} consistent for their population counterpart uniformly with respect to the cross-sectional dimension.

Once these assumptions are settled, we can estimate the exact factor model as a possibly misspecified approximation of the model (as in equation 2). We can prove that misspecification effects disappear as $T, n \rightarrow \infty$. The model can be approximated as explained in the previous section:

- i. Equation (4) is an $(r \times r)$ filter of finite length p with roots outside the unit circle, and ν is a Gaussian white noise, $\nu_t \sim i.i.d.N(0, I_r)$.
- ii. The idiosyncratic component are cross sectionally independent gaussian white noise, $e_{it} \sim i.i.d.N(0, \zeta_d)$, where ζ_d is the diagonal matrix. Necessary for maintaining parsimony and identification.

Under these assumptions, they can cast the model in a state-space form with the number of states equal to the number of common factor r . The likelihood can then be evaluated recursively using the Kalman filter for any set of parameters.

$$\hat{F}_{\hat{\theta}} = E_{\hat{\theta}}[F|X] \tag{9}$$

Doz, Giannone, Reichlin (2012) [39] proved that principal components can be achieved as a special case, if the following assumption are followed:

$$\begin{cases} \psi_{ij} = 0 & \forall i, j \\ \beta_i = 0 & \forall i \\ \sigma_i^2 = 0 & \forall i \end{cases} \quad (10)$$

Expectation-Maximization algorithm implemented following these phases. In the first phase, the algorithm computes the principal components. The model parameters are estimated using OLS regression, treating the principal components as true common factors. In the second phase, the Kalman smoother is used to update the estimates. Maximum likelihood is achieved by iterating the two phases until convergence, accounting for the uncertainty associated with the fact that factors are evaluated at each step. It has been proved by Doz et al. (2012) [39] that this approximate factor model is robust to misspecification of the cross-correlation between the idiosyncratic components and the estimates are robust to non-gaussianity¹¹.

2.1.4 Block structure

In Miranda-Agrippino & Rey (2015) [64], when estimating the Global Financial Factor, they decompose the risky assets into asset-specific, regional and global components to model the correlation the within the group of risky assets. Later, Delle Chiaie (2017) [37] drew inspiration from these authors, and their local factors have been extracted from different categories of commodities. Similarly, we determine the number of blocks to be included in the model following the IMF commodity database, which is summed up in Table 1. As an outcome, we extract two main block factors (energy and non-energy), three sub-blocks (fertilizers, industrial inputs, food and beverages) and ultimately, eight group factors (crude oil, natural gas, coal, food, beverages, agricultural raw materials, metals and precious metals). However, we have a more extensive set of price series and brand new groups of commodities; therefore, we require a deeper structure to exploit the local correlation within the block, model the idiosyncratic components and then extract the common component from the commodities.

For what concerns the number of global factors, we follow the guidelines of Delle Chiaie (2017) [37], where they decided the number of global factors according to the information

¹¹Their paper follow the model as in White (1982) [74]

criterion (IC) for quasi-maximum likelihood function as in Doz et al.(2012) [39], which is the modified version of the IC test by Bai and Ng (2002) [4]. Bai and Ng (2002) [4] provided a penalty function to select the optimal number of factors to approximate factor models when the factors are estimated by principal component. For the quasi-maximum likelihood function, Doz et al.(2012) [39] proved that the convergence rate for the factor estimates can be written as in equation (11), therefore the IC of Bai and Ng (2002) [4] becomes as in equation (12):

$$C_{nT}^{*2} = \min\{\sqrt{T}, (n/(\log(n)))\} \quad (11)$$

$$IC^*(r) = \log(V(r, F_{(r)})) + rg(n, T) \quad (12)$$

$$g(n, T) = ((\log(C_{nT}^{*2}))/C_{nT}^{*2}) \quad (13)$$

In equation 12, T is the number of sample observations, r represents the number of global factors, $F_{(r)}$ are the extracted factors, the function $V(r, F_{(r)})$ consists in the sum of squared idiosyncratic components divided by nT . Equation (13) is the penalty function for over-fitting¹². Della Chiaie et Al.(2017) [37] proved that lowest IC is achieved with one global factor, therefore we follow their lead.

2.2 Dynamic factor model results

2.2.1 The Common Commodity Factor

In Figure 4 we report the Global Factor -or common commodity factor (CCF) - extracted from real prices along with the IMF commodity index. CCF has been normalized, and it positively correlates with the global business cycle. The IMF index is a weighted average of the commodity prices, with weights as reported in Table 6 and computed as explained in section 2.1.1. The IMF broad index is cross-sectional average, and it tends to approximate the global factor reasonably well if the idiosyncratic disturbances have limited cross-correlation, Forni & Reichlin (1998)[46]. Although, In reality, idiosyncratic components in simple averages may raise a relevant noise component.

Our factor¹³ with respect to the up-to-date IMF index, captures less swift fluctuation next to oil price crisis, e.g., Gulf war or Covid-19, and financial crisis¹⁴; this suggests that

¹²Coroneo et Al. [33] applied this method in their paper

¹³The CCF is highly correlated with our replica of the global factor -with updated data- proposed by Della Chiaie (2017). $\rho : 0.96281$.

¹⁴Shaded areas in Figure 4 represent periods of widespread recession. More details on the notes below

our factor is more stable than IMF. The correlation between the CCF and IMF index is displayed in Figure 4, $\rho : 0.68$ ¹⁵. Worth to notice that the 2014-2016 IMF weights put much lower importance on energy commodities which are the ones with the highest volatility. When the 2002-2004 IMF weights put about 60% of weight on the energy commodities, this is due to the 2000s commodity boom, and it will be an object of discussion later.

As suggested in the paper of Della Chiaie (2017)[37], the CCF is a pervasive shock that affects a large cross-section of commodity prices; therefore, it captures the movements of worldwide demand for commodities associated with the business cycle. If this is true our factor should positively correlate with world trade index. We decide to model the CCF following Miranda-Agrippino & Rey (2021) [61], Doz, Giannone & Reichlin (2011) [40] and Bai & Ng (2004) [3], the factor is obtained via cumulation of factors estimates on the stationary and first-difference (log) price series¹⁶; in figure 5 we plot the resulting commodity factor along with world trade index(from the CPB World Trade Monitor). As we can notice the two variables co-move and are strongly correlated, $\rho : 0.847$. To make this idea more straightforward, we expressed the CCF as year-on-year growth rate, and plot in the top panel the Figure 6 we plot the CCF along with Killian (2009) [56] index of economic activity¹⁷, while in the bottom panel of the figure, we plot the CCF along with Baumaister and Hamilton (2019)[9] measure of economic activity¹⁸. The results in Figure 6 are positively correlated¹⁹ in both panels and follow the business cycle in the phases of contraction and recession. The strong correlation between the CCF and the world industrial production is in line with the idea of Killian (2017) [58], that broad-based indices of commodity prices are a leading indicator of the global industrial production. The CCF captures the macroeconomic expansion of the early 2000s in parallel with the

the Figure 4.

¹⁵If we use nominal data, the correlation differs. $\rho : 0.70$

¹⁶In Bai & Ng (2004) [3], given the differenced stationary series $x_{it} = \Delta X_{it}$, idiosyncratic error as $z_{it} = \Delta e_{it}$ and $f_t = \Delta F_t$, the model in its first-difference form is $x_{it} = \lambda'_i f_t + z_{it}$, once obtained: the estimated factors \hat{f}_t , associated loadings $\hat{\lambda}_i$ and residuals $\hat{z}_{it} = x_{it} - \hat{\lambda}'_i \hat{f}_t$. With $t = 2, \dots, T$ we can

define \hat{F}_t in the following way: $\hat{F}_t = \sum_{s=2}^t f_s$

¹⁷The index proposed in Killian (2009)[56] is a measure for the part of global real economic activity that drives demand for industrial commodities on global commodity markets. The index was created using single-voyage dry cargo ocean freight rates and is specifically designed to reflect fluctuations in industrial commodity demand caused by the global business cycle.

¹⁸It is a more comprehensive version of the OECD's monthly industrial output index for the OECD and six other important nations. According to the IMF World Economic Outlook, the nations in their index account for 79% of worldwide petroleum product consumption and 75% of global GDP, according to the IMF World Economic Outlook.

¹⁹The correlation between the CCF and Killian index is 0.54, and the correlation between CCF and WIP is 0.71

commodity boom. Between 2011 and 2016, the CCF shows a small fall, which has been described by Kilian & Zhou (2018) [58] as a more sluggish Chinese demand for industrial commodities. We are going to discuss this case later.

In the top panel of the figure 7 we plot our factor along with the Global Financial Uncertainty factor (GFU) of Caggiano & Castelnuovo (2021) [17], while in the bottom panel, we plot the Global Financial Factor (GFC) of Miranda-Agrippino, Nenova & Rey (2020) [62]. As discussed earlier, uncertainty is countercyclical; during recession periods, uncertainty tends to be high and low during economic growth, macroeconomic and financial stability. However, as we can see in the graph, the uncertainty seems to be high near the major global crisis, leading to a turmoil in the commodity factor, such as the Great Recession and Covid-19. In the second panel of Figure 7, the two factors are strongly correlated and comove similarly. In Miranda-Agrippino & Rey (2021) [61], they check for the correlation between their factor and other global factors; they also check for the correlation between the commodity prices and the GFC, which was about 0.24. The correlation between our factor and the GFC is stronger ($\rho : 0.508$). The previous figures confirm the idea that the CCF and the demand for commodities follow the business cycle. During expansion periods the demand increase, first, directly via demand for industrial inputs, second, indirectly via general equilibrium effects, and vice-versa during recession periods. The evidence that CCF has similar impacts on all commodity prices further supports the idea that global demand and CCF are strongly linked. In Figure 8 we illustrate this by plotting the loadings on the global factor λ_i . The figure shows that the global factor affects commodity prices similarly and produces identical price reactions because factor loadings all have similar values and signs. These results suggest that the global factor has a modest influence on relative pricing when taken collectively. This finding is in line with Barsky and Kilian (2002) [8]. To further prove this point, in Figure 11 we use an example based on the pairwise relationship between oil and copper prices. In the top panel of the figure, The dashed lines represent the commodity prices, while the solid lines represent the fit based on the CCF. Although the fitted value tracks both markets incredibly well and the variations are nearly identical, if we look at the bottom panel of the figure, there are significant price fluctuations in their relative values, which are not captured by the common factor. The latter can be seen by the poor fit between the relative prices and the relatively common component; this mismatch can be largely attributed to a commodity-specific or market-specific factor. In Figure 9 we re-estimate the model using nominal prices and it does not display significant differences. Moreover, we asked

ourselves whether the factor is sensitive to sample changing; in Figure 10 we estimate the factor using a smaller sample (92m1-19m11) which excludes two critical episodes, the Gulf war in 1990-1991 and the Covid-19 in 2020-2021, and the factor does not display relevant changes.

2.2.2 Historical variance decomposition

As we mentioned in the previous section, the CCF (or global factor) reflects movements in demand for commodities that arise with the business cycle. Other block factors and idiosyncratic components prevent a commodity-specific shock from spreading to other markets, limiting the impact on other commodities in the same category. Therefore, we can disentangle these three parts to explain commodities' price change thanks to the block structure. In this subsection, we are going to explore a historical decomposition of various events that affected commodity prices, especially oil prices.

2000s commodities boom A wide range of literature agrees that the commodity price boom of 2003 to mid-2008 is primarily due to China's economic development and its crude oil consumption, Hamilton (2009) [50][51]. In 2003 China's GDP was growing at a 7% rate per year, along with their crude oil consumption. In 2007, Chinese consumption reached 870,000 barrels per day, greater than in 2005. Even if more oil was consumed, no more oil was being produced. Simple macro 1-o-1 teaches us that if in a region the consumption increase, somewhere else, the consumption has to decline. Therefore prices had increased enough to reduce the consumption in the OECD countries to offset the increase in demand in China. Moreover, another determinant of oil price increase was the inability of *Saudi Arabia* in 2005-2007 of adjusting the oil supply to the increasing demand. Before 2005, people expected that the Saudis would continue to exploit their spare capacity to buffer the consequences of short-term supply shortages in response to the longer-term pressures of rising global demand. This did not happen in that situation. The results in 2007 were that the consumption in the United States was 122,000 barrels per day, lower than in 2005; in Europe, consumption fell 346,000 b/d, while in Japan, consumption fell 318,000 b/d. Clearly, China's economic growth did not solely affect the oil prices, but it can be extended to many other primary commodities. China had to satisfy the increasing demand for energy for production; therefore, China and Taiwan renewed their interest in coal and energy companies. Moreover, crop food prices rose because of the rise in population and the increasing interest in biofuel. We decide to plot in Figure 12 the historical decomposition of some commodities with a high level of trade, that are Brent crude Oil, copper, maize and nickel. The red bars, blue and grey bars are, respectively, the cumulative effect of the common factor (CCF), the block specific and idiosyncratic error. Starting from 2003, most of the increase in the oil prices is explained

by the global factor, while the block-specific factor explains only a smaller part of the variation. This is in line with the finding of Baumeister & Peersman (2013) [11], which attributes the reason for global price shifts to global demand shocks. Aside from the Oil price movements, also the other commodities were largely affected by the CCF in 2003, implying that commodity prices have reacted to the same economic fundamentals, Delle Chiaie et al. (2017) [37]. Since we introduced precious metals inside our dynamic factor model, we are interested in retrieving some insights on gold, which accounts for about 10% of total trade in 2015. In Figure 13 there is the historical decomposition of gold for the period 2000-2014. Until 2005, the price increase was mostly explained by the CCF. Then as mentioned before, the precious metal became a safe heaven asset and the market boomed; therefore, the block-specific factor became relatively more important in explaining the price movement, especially after 2008.

The Gulf War A Historical event that affected global oil production was the Gulf war, which happened between July 1990 and March 1991. The USA waged war in response to Iraq's annexing of Kuwait in August 1990. Kuwait's oil output was over its necessary OPEC quota throughout the previous decades, keeping world oil prices low. Iraq regarded Kuwait's unwillingness to reduce its oil output as an act of hostility against the Iraq economy, which led to the invasion. In the top-left panel of Figure 14 we can see the historical decomposition of the prices. This is one oil block-specific case; therefore, the macroeconomic conditions and the global factor have a negligible effect on the shift in oil prices since this is a clear case of oil supply shortening and inventory demand increase.

The Great Recession As we discussed in *2000s commodity boom paragraph*, before the great recession, various factors led to an increase in commodity prices. When the financial crisis happened, it was followed by a large economic contraction worsened by high commodity prices. As we can see from the top right panel of the Figure 14 the fall in oil prices was primarily due to business cycle conditions.

The Oil price fall In 2014, an unexpected oil price fall happened. This price drop has put a great economic strain on oil producers worldwide. It has also harmed the fiscal stability of nations that rely substantially on foreign cash earnings from crude oil exports, such as Iran, Russia and Venezuela, while delivering a boost to numerous net oil importers. According to Baumeister & Killian (2016) [10], the fall in prices is due in July

was primarily due to a weakening of the global economy and then an associated lower demand for inventory in December 2014. As we can see from the bottom-left panel of Figure 14, The CCF has a larger cumulative impact at the beginning of the series, but the block-specific factor becomes more relevant through time. This is in line with the OPEC's decision in November 2014 to maintain existing production levels despite non-OPEC oil output rising steadily.

Covid-19 The most recent crisis that affected GDP and the oil prices was the covid-19 in 2020. In parallel with quarantines and industrial production constrained, oil producers remained with a large surplus of inventories, struggling to store the oversupply. According to the bottom-right panel in Figure 14, the most relevant case for price fall was an oversupply, as the oil price fall of 2014. Economic recession, hence the CCF, explains only a little part of the oil price decrease during the pandemic (03/20-05/20) while becoming more relevant in 2021 with the economic recovery.

3 VAR Analysis

3.1 Econometric framework

To answer the questions we introduced in Section 1, we use the VAR analysis, which has become one of the most used tools for analyzing the dynamics of an economic system since the influential work of Sims (1980) [71]. The vector autoregressive (VAR) framework provides a straightforward method to capture dynamics in multiple time series, allowing macroeconometricians to describe, summarize, and forecast macroeconomic data and quantify the underneath structure of the economy, Stock & Watson (2001) [72]. Two of the major uses of the VAR are for quantifying the impulse responses to macroeconomic shocks to retrieve the forecasted error variance decomposition to understand the contribution of each shock to the fluctuation of the other variables.

3.1.1 Vector Autoregression

A Vector Autoregressive (VAR) can be expressed as a linear model with n -equations, n -variables and p lags; where, each variable, is explained by its own lagged values as well as the present and previous values of the remaining $n - 1$ variables. Given $x_t = (x_{1t}, \dots, x_{nt})'$ is an $(n \times 1)$ vector containing the values that n variables assumes at date t and $e_t = (e_{1t}, \dots, e_{nt})'$ are the errors with mean zero. Further assume that the series x_t are covariance stationary, that means: constant mean $E[x_{it}] = \mu_i$, constant variance $va[x_{it}] = \sigma_i^2$, constant autocovariance $cov[x_{it}, x_{it+\tau}] = \gamma_i(\tau)$. For each x_t we can give the VAR(1) representation:

$$x_t = \alpha_1 x_{t-1} + e_t \tag{14}$$

We can further transform Equation 14 into a structural vector autoregression (SVAR) and achieve a more clear interpretation of the data.

$$\beta_0 x_t = \phi_1 x_{t-1} + \varepsilon_t \tag{15}$$

$$x_t = \phi_1 x_{t-1} + \beta_0^{-1} \varepsilon_t \tag{16}$$

Equation 16 can have a matrix representation:

$$\begin{bmatrix} x_{1t} \\ \vdots \\ x_{nt} \end{bmatrix} = \begin{bmatrix} \phi_{11} & \dots & \phi_{1n} \\ \vdots & \ddots & \vdots \\ \phi_{n1} & \dots & \phi_{nn} \end{bmatrix} \begin{bmatrix} x_{1t-1} \\ \vdots \\ x_{nt-1} \end{bmatrix} + \begin{bmatrix} b_{11} & \dots & b_{1n} \\ \vdots & \ddots & \vdots \\ b_{n1} & \dots & b_{nn} \end{bmatrix} \begin{bmatrix} \varepsilon_{1t} \\ \vdots \\ \varepsilon_{nt} \end{bmatrix} \quad (17)$$

The linear representation is the following:

$$\begin{cases} x_{1t} = \phi_{11}x_{1t-1} + \phi_{12}x_{2t-1} + \dots + b_{11}\varepsilon_{1t} + b_{12}\varepsilon_{2t} + \dots \\ x_{2t} = \phi_{21}x_{1t-1} + \phi_{22}x_{2t-1} + \dots + b_{21}\varepsilon_{1t} + b_{22}\varepsilon_{2t} + \dots \end{cases} \quad (18)$$

It is fundamental to notice that $e_t = \beta_0^{-1}\varepsilon_t$. And that, ε_t in equation 16, are the unobservable shocks and the last two terms in equation 18, are the linear representation. It follows that β_0^{-1} is the impact matrix of the shocks, which is what we are concerned to find. A common assumption is that the vector of shocks, $\varepsilon_t = (\varepsilon_{1t}, \dots, \varepsilon_{nt})'$ is a zero mean white noise process, namely $\varepsilon_t \sim WN(0, I_n)$, with serially uncorrelated and independent shocks. That is:

$$\Sigma_\varepsilon = \begin{bmatrix} 1 & \dots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \dots & 1 \end{bmatrix} \quad \text{and} \quad \gamma_\varepsilon = \begin{bmatrix} 1 & \dots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \dots & 1 \end{bmatrix} \quad (19)$$

Moreover note that from VAR equation 15 and SVAR equation 16 we can substitute recursively and obtain the following moving average (MA) constructions:

$$\begin{cases} x_t = \theta_0 e_t + \theta_1 e_{t-1} + \dots \\ x_t = \psi_0 \varepsilon_t + \psi_1 \varepsilon_{t-1} + \dots \end{cases} \quad (20)$$

In matrix form we have:

$$\begin{cases} x_t = \Theta_j e_t \\ x_t = \Psi_j \varepsilon_t \end{cases} \quad (21)$$

Recalling:

$$e_t = \beta_0^{-1}\varepsilon_t \quad (22)$$

Combining equations in 21 and equation 23 we get:

$$\Psi_j = \Theta_j \beta_0^{-1} \quad (23)$$

By finding φ_j we would be able to find the response of x_{t+g} to a ε_t shock. Note that φ_j and β_0^{-1} cannot be retrieved so easily since ε_t is unobservable. Although α_1 can be

easily computed by regressing x_t on x_{t-1} , as a consequence we can retrieve e_t , and the MA of x_t as in the first line of equation 20. Therefore if someone knows ψ_0 , we can retrieve all the Ψ_j .

3.1.2 Impulse Responses

Impulse response functions (IRFs) trace the response of present and future values of each variable to a unitary increase in the value of one of the VAR shocks ε_{jt} at time t , assuming that it will return to zero in the subsequent periods, and keeping all other shocks constant at value zero. When the error terms are uncorrelated across equations, the suggested thought experiment of altering one error while keeping the others constant makes the most sense; hence impulse responses are commonly computed for recursive and structural VARs. Now, taking into consideration a reduced-form VAR(1) with $n = 2$ which are gdp and interest rates. and assume we have already the OLS estimate of $\hat{\alpha}$ and \hat{e}_t :

$$\begin{bmatrix} y_t \\ r_t \end{bmatrix} = \begin{bmatrix} \alpha_{11} & \alpha_{12} \\ \alpha_{21} & \alpha_{22} \end{bmatrix} \begin{bmatrix} y_{t-1} \\ r_{t-1} \end{bmatrix} + \begin{bmatrix} e_{yt} \\ e_{rt} \end{bmatrix} \quad (24)$$

The reduced form innovations e_t in equation 24 are not going to help us in answering the question what is the effect of a monetary policy shock on gdp growth. The Structural VAR model came in handy, we can assume that the model of the economy is given by:

$$\begin{bmatrix} y_t \\ r_t \end{bmatrix} = \begin{bmatrix} \phi_{11} & \phi_{12} \\ \phi_{21} & \phi_{22} \end{bmatrix} \begin{bmatrix} y_{t-1} \\ r_{t-1} \end{bmatrix} + \begin{bmatrix} b_{11} & b_{12} \\ b_{21} & b_{22} \end{bmatrix} \begin{bmatrix} \varepsilon_t^y \\ \varepsilon_t^r \end{bmatrix} \quad (25)$$

and according to equation 23, obviously the reduced form innovations can be written as a linear combination of the two structural shocks:

$$\begin{cases} e_{yt} = b_{11}\varepsilon_t^y + b_{12}\varepsilon_t^r \\ e_{rt} = b_{21}\varepsilon_t^y + b_{22}\varepsilon_t^r \end{cases} \quad (26)$$

Recall that e_{rt} is not the monetary policy shock. For example, a positive variation in e_{rt} may be due to a positive GDP shock that increases either the output or the interest rate; that is the case when $b_{21} > 0$. Conversely, a positive variation in e_{rt} may be due to a monetary policy shock that decreases output growth and increases the policy rate, $b_{22} > 0$. The nature of the identification problem evolves around disentangling which shocks cause a variation in e_t .

Therefore we need to find a mapping between the reduced form VAR and its structural counterpart. To do so we can exploit relationship between reduced form and structural innovation from equation 23. The variance-covariance matrix of the innovation becomes:

$$\Sigma_e = E[e_t e_t'] = E[\beta \varepsilon_t (\beta \varepsilon_t)'] = [\varepsilon_t \varepsilon_t'] = \beta \Sigma_\varepsilon \beta' = \beta \beta' \quad (27)$$

Therefore:

$$\Sigma_e = \beta \beta' \quad (28)$$

The solution to our problem is restricted to finding β , although this is not easy because there exists an infinite combination of β that results in the same Σ_e . If we expand the matrices in equation 28

$$\begin{bmatrix} \sigma_{yy}^2 & \sigma_{yr}^2 \\ \sigma_{ry}^2 & \sigma_{rr}^2 \end{bmatrix} = \begin{bmatrix} b_{11} & b_{12} \\ b_{21} & b_{22} \end{bmatrix} \begin{bmatrix} b_{11} & b_{21} \\ b_{12} & b_{22} \end{bmatrix} \quad (29)$$

This can be rewritten as a system of linear equations in the following way:

$$\begin{cases} \sigma_{yy}^2 = b_{11}^2 + b_{12}^2 \\ \sigma_{yr}^2 = b_{11}b_{21} + b_{12}b_{22} \\ \sigma_{ry}^2 = b_{21}b_{11} + b_{22}b_{12} \\ \sigma_{rr}^2 = b_{21}^2 + b_{22}^2 \end{cases} \quad (30)$$

As we know, the matrix Σ_e is symmetrical, and therefore in the system of equation 30, the second and third equations are identical. This implies that we have four unknowns and three equations. For a general n -VAR model, the identification problem is that we have n^2 unknowns and $n(n - 1)$ equations.

This is the part where economic theory comes in handy. We can assume the economy's structure to add missing equations to our model. The extra equations reduce the number of infinite β matrices to a single, or few, that satisfy your assumption. Different kinds of restrictions can be adapted to deal with this problem: Zero-long run restriction, sign restriction, external instruments, narrative sign restrictions, combining sign restrictions and instruments, etc. Since the idea of this thesis is not to explain each of these methods deeply, we are going to focus on the identification scheme we choose, which is the zero short-run restrictions or Cholesky identification.

Cholesky identification This identification scheme was proposed by Sims (1980) [71] and review from Christiano et Al. (1999) [32]. We can assume that monetary policy shock has no contemporaneous effect on output in our example. This implies that b_{12} that captures the effect of the monetary policy on output is zero. β matrix changes and the equation 25 becomes:

$$\begin{bmatrix} y_t \\ r_t \end{bmatrix} = \begin{bmatrix} \phi_{11} & \phi_{12} \\ \phi_{21} & \phi_{22} \end{bmatrix} \begin{bmatrix} y_{t-1} \\ r_{t-1} \end{bmatrix} + \begin{bmatrix} b_{11} & 0 \\ b_{21} & b_{22} \end{bmatrix} \begin{bmatrix} \varepsilon_t^y \\ \varepsilon_t^r \end{bmatrix} \quad (31)$$

Now that we have 3 parameters and 3 equation, β is a lower triangular and ,keeping in mind equation 26, Σ_e represents the Cholesky decomposition:

$$\Sigma_e = \begin{bmatrix} \sigma_{yy}^2 & \sigma_{yr}^2 \\ \sigma_{ry}^2 & \sigma_{rr}^2 \end{bmatrix} = \begin{bmatrix} b_{11} & 0 \\ b_{21} & b_{22} \end{bmatrix} \begin{bmatrix} b_{11} & b_{21} \\ 0 & b_{22} \end{bmatrix} \quad (32)$$

In linear form becomes:

$$\begin{cases} \sigma_{yy}^2 = b_{11}^2 \\ \sigma_{yr}^2 = b_{11}b_{21} \\ \sigma_{rr}^2 = b_{21}^2 + b_{22}^2 \end{cases} \quad (33)$$

and the solution is:

$$\begin{cases} b_{11}^2 = \sigma_{yy} \\ b_{21} = \sigma_{yr}^2 / \sigma_{yy} \\ b_{22} = \sqrt{\sigma_{rr}^2 - (\sigma_{yr}^2)^2 / \sigma_{yy}^2} \end{cases} \quad (34)$$

At this point we can substitute the results in equation 34 into equation 35, and obtain:

$$\begin{bmatrix} y_t \\ r_t \end{bmatrix} = \begin{bmatrix} \phi_{11} & \phi_{12} \\ \phi_{21} & \phi_{22} \end{bmatrix} \begin{bmatrix} y_{t-1} \\ r_{t-1} \end{bmatrix} + \begin{bmatrix} \sigma_{yy} & 0 \\ \sigma_{yr}^2 / \sigma_{yy} & \sqrt{\sigma_{rr}^2 - (\sigma_{yr}^2)^2 / \sigma_{yy}^2} \end{bmatrix} \begin{bmatrix} \varepsilon_t^y \\ \varepsilon_t^r \end{bmatrix} \quad (35)$$

By assumption we know that the impact effect of one standard deviation of ε_t^r on GDP is zero, while on interest rate is equal to $\sqrt{\sigma_{rr}^2 - (\sigma_{yr}^2)^2 / \sigma_{yy}^2}$. While one standard deviation shock of ε_t^y on gdp is equal to σ_{yy}^2 , on interest rate is $\sigma_{yr}^2 / \sigma_{yy}$.

As said before, this identification scheme evolves around the fact that exists a lower triangular P such that $\Sigma_e = PP'$, and according to our assumptions, also β is now lower triangular. This implies that $P = \beta$.

As we can understand, we need to make strong assumptions about the economy's structure. Therefore, we have to justify why some variables have an immediate impact on

the other variables and others respond with a lag. Nowadays, the most common assumption among the economists is the existence of fast-moving, therefore respond immediately to a shock, and slow-moving variables that respond with a lag²⁰. We are going to discuss, in the following section, how we structured our identification.

3.1.3 Forecast error variance decomposition

According to Stock Watson (2001) [72], The forecast error decomposition (FEVD) is the portion of variance of the error term e_t , made in estimating a variable, attributable to a certain structural shock ε_{jt} at a specified horizon h . The variance decomposition gives the relative importance of each structural shock in affecting the forecast error variance of the VAR's endogenous variables. For example, We can ask ourselves how much demand shocks contribute to driving GDP forecasted errors. The change in a variable that could not have been foreseen between $t - 1$ and $t + h$ attributable to the realization of structural shocks is the forecast error of a variable at horizon $t + h$. In a practical example:

$$\begin{aligned}
 h = 0 \quad x_t - E_{t-1}[x_t] &= \phi x_{t-1} + \beta \varepsilon_t - \phi x_{t-1} = \beta \varepsilon_t \\
 h = 1 \quad x_{t+1} - E_{t-1}[x_{t+1}] &= \phi x_t + \beta \varepsilon_{t+1} - \phi^2 x_{t+1} \\
 &= \phi(\phi x_{t-1} + \beta \varepsilon_t) + \beta \varepsilon_{t+1} - \phi^2 x_{t+1} \\
 &= \phi \beta \varepsilon_t + \beta \varepsilon_{t+1}
 \end{aligned} \tag{36}$$

So the FEVD becomes for every horizon h :

$$FE_{t+h} = x_{t+h} - E_{t-1}[x_{t+h}] = \sum_{i=0}^h \phi^{h-i} \beta \varepsilon_{t+i} \tag{37}$$

Now we can compute the variance of FE_{t+h} , for simplicity let's compute it for $h = 0$. Recalling from equation 19 that shocks are orthogonal to each other. The variance of the FE becomes:

$$\begin{aligned}
 var(y_t - E_{t-1}[y_t]) &= b_{11}^2 var(\varepsilon_t^y) + b_{12}^2 var(\varepsilon_t^r) = b_{11}^2 + b_{12}^2 \\
 var(r_t - E_{t-1}[r_t]) &= b_{21}^2 var(\varepsilon_t^y) + b_{22}^2 var(\varepsilon_t^r) = b_{11}^2 + b_{12}^2
 \end{aligned} \tag{38}$$

²⁰This was argued from Bernanke and Mihov (1998) [13] when trying to identify the effect of a monetary policy shock.

Now we can properly compute the FEVD and answer our questions for $h = 0$:

$$\left\{ \begin{array}{l} FEVD_{y_0}^{\varepsilon^y} = \frac{b_{11}^2}{b_{11}+b_{12}} \\ FEVD_{y_0}^{\varepsilon^r} = \frac{b_{12}^2}{b_{11}+b_{12}} \end{array} \right. \quad \left\{ \begin{array}{l} FEVD_{r_0}^{\varepsilon^y} = \frac{b_{21}^2}{b_{11}+b_{12}} \\ FEVD_{r_0}^{\varepsilon^r} = \frac{b_{22}^2}{b_{21}+b_{22}} \end{array} \right. \quad (39)$$

Note that $FEVD_{r_0}^{\varepsilon^y}$ and $FEVD_{r_0}^{\varepsilon^r}$, and similarly for the variance decompositions of the output, sum up to 1. In this $n = 2$ VAR a portion of the variance in the error term is explained by the output and the rest on the interest rate.

3.2 VAR: Data, identification, results

Now that we have illustrated the tools we are going to use for the VAR analysis, it is time to apply them. First, we are going to describe the data used, and then we are going to show and discuss the resulting IRFs and the FEVDs for the two samples as in Hoesch, Rossi and Sekhposyan (2021) [52] to discuss the *information channel*.

3.2.1 VAR: Dataset

In Table 5 there is a brief description of the data we insert into the VAR. We download American variables such as CPIAUCSL, INDPRO and FEDFUNDS from FRED Website²¹. The world industrial production index (WIP) is provided by Baumaister and Hamilton (2019) [9], and it is a more comprehensive version of the OECD's monthly industrial output index for the OECD and six additional important nations; the nations included in their index account for 79% of worldwide petroleum product consumption and 75% of global GDP. We use the cumulative CCF as in figure 5. Caggiano and Castelnuovo (2021) [17] provided the global financial uncertainty (GFU). We use the updated version of the Global financial cycle index (GFC), computed in Miranda-Agrippino, Nenova and Rey (2020) [62]. All the data are monthly. We adopted a logarithmic transformation on the variables that display trends²², in our case: INDPRO, CPIAUCSL, WIP. The data in the Effective Federal Fund Rate between 2008m12 and 2015m12 have been substituted with the Shadow Rate²³ of Wu & Xia (2016) [75]. The reason behind this decision is that FED has traditionally utilized the federal funds rate as the principal instrument of

²¹Federal Reserve Economic Data (FRED): <https://fred.stlouisfed.org/>.

²²A simple way to change a highly skewed variable into a more normalized dataset is to use logarithmic transformation.

²³More details in section 1.1

monetary policy, reducing it to offer greater stimulus and raising it to limit economic activity and manage inflation. However, from 2008m12 to 2015m12, the rate reached the ZLB (zero lower bound), and the FED was incapable of providing further stimulus to the economy with traditional monetary policy. As a result, the Fed has resorted to unconventional monetary policy such as quantitative easing and forward guidance to impact long-term interest rates. Therefore, while the FF rate is at the zero lower bound, it does not deliver much information about policies adopted. On the other hand, the shadow federal funds rate delivers vital and economically relevant information because it summarizes conventional and, especially, unconventional monetary policies. As a matter of fact, since the federal funds rate cannot be negative, during the period 2008m12-2015m12, the Shadow rate does.

3.2.2 VAR: Identification set-up

The first VAR we are going to analyze has 12 lags, constant and linear trends, and it is estimated over the sample 1992m7-2019m4. While, the second VAR is estimated over the sample 1992m7-2019m4. As we said in section 3.1.2 when we apply the Cholesky identification scheme, we have to make some assumptions about the state of the economy; therefore, we have to choose the ordering of the variables carefully. Because the impact matrix β , under zero-contemporaneous restriction, becomes a lower triangular and not all shocks affect the other variables contemporaneously. However, some variables are affected by the shock with a lag. To clarify this point, take into consideration equation 23 with n variables, which map the shocks to the innovations of the reduced form VAR; at time t , the first row variable innovation observe only its own shock, eg. $u_t^1 = b_{11}\varepsilon_t^1$, the second variable innovation observe itself and the shock of the first variable, eg. $u_t^2 = b_{21}\varepsilon_t^1 + b_{22}\varepsilon_t^2$, and so on. In our case, the β matrix of our seven variables SVAR is the following:

$$\begin{bmatrix} b_{uu} & 0 & 0 & 0 & 0 & 0 & 0 \\ b_{fu} & b_{ff} & 0 & 0 & 0 & 0 & 0 \\ b_{wu} & b_{wf} & b_{ww} & 0 & 0 & 0 & 0 \\ b_{cu} & b_{cf} & b_{cw} & b_{cc} & 0 & 0 & 0 \\ b_{iu} & b_{if} & b_{ic} & b_{iw} & b_{ii} & 0 & 0 \\ b_{pu} & b_{pf} & b_{pc} & b_{pw} & b_{pi} & b_{pp} & 0 \\ b_{ru} & b_{rf} & b_{rc} & b_{rw} & b_{ri} & b_{rp} & b_{rf} \end{bmatrix} \begin{bmatrix} \varepsilon_t^{GFU} \\ \varepsilon_t^{GFC} \\ \varepsilon_t^{WIP} \\ \varepsilon_t^{CCF} \\ \varepsilon_t^{INDPRO} \\ \varepsilon_t^{CPI} \\ \varepsilon_t^{FF} \end{bmatrix} \quad (40)$$

To identify monetary policy shock, we follow the idea of a reaction function, or feedback rule, as suggested by Taylor (1993) [73]. The concept of the feedback rule evolves around the idea that a large portion of the variation in central bank policy actions is due to policymakers' systematic reactions to changes in the economy. We followed Christiano et Al. (1999) [32] and ordered the effective federal funds rate last, right after industrial production and consumer price index. Although in our case, the FED does not react solely to USA's real economy but add to its information set also the global variables in an attempt to anticipate repercussion to the American economy. To identify the common commodity factor shocks, we develop the idea we said in section 2.2.1, that is, the CCF capture the shifts in the demand for commodities associated with the global business cycle. Therefore, we assumed that CCF responds to the global variables: WIP, GFC and GFC. We decided to put the GFU in the first position since there are empirical evidence from Angelini, Bacchiocchi, Caggiano, and Fanelli (2019) [2] and Ludvigson et Al. (2021) [59], that uncertainty stemming from financial markets is an exogenous and relevant driver of the business cycle²⁴.

3.2.3 VAR: Full Sample Analysis

In the following paragraphs, there are the impulse response functions over the full sample, 1992m7-2019m4, for the three shocks, that the literature thinks are the most relevant driver of the global financial cycle and world output.

Global Financial Uncertainty Shock As we can see from Figure 15, our results confirms the recessionary effect of the of the uncertainty literature, eg. Bloom (2014) [14], Castelnuovo (2019) [28], Caggiano, Castelnuovo (2021) [17]. After a GFU shock, there is a large negative impact on the GFC, which recovers slowly after 30 months. Industrial production and world industrial production display similar trends; they decrease after the shock reaching the rock bottom around the 12th month; industrial production recovers after the 24th month, while the world output after the 30th stay in mild conditions. Consumer price index decreases in response to the recessionary effect of the uncertainty. Federal funds rate decrease as a consequence of the shock to offset its recessionary effects, in line with the findings of Castelnuovo (2019) [29] and Ludvigson et Al. (2021) [59]. Interestingly, the CCF has a negative impact that worsens in the following years, there

²⁴It has been shown in both paper that also macroeconomic uncertainty is an exogenous and relevant driver of the business cycle.

are symptoms of reprise only after twelve months, but it never returns to pre-shock levels.

Common Commodity Factor Shock Figure 16 reports the IRFs to a shock of the CCF for the sample 1992m7-2019m4. The Commodity factor does not display an immediate recessionary effect on the global variables. The CCF, being associated with higher activity in the business cycle in the short run, improves the global financial cycle and world output, but uncertainty remains in mild conditions. The IRFs of the American variables show symptoms of an economic slowdown. CPI increases on impact, while the output falls over time due to higher prices of the products and production costs (stagflation). FED does not respond strongly until the 14th month is static. In correspondence to the eighth month, all variables present recessionary fluctuations: Uncertainty spikes, GFC and WIP decrease, CCF returns in mild conditions, CPI returns to zero, INDPRO further decreases and FED, as said earlier, decreases. Uncertainty and GFC are the only variables that recover shortly after.

Federal Funds Rate Shock In Figure 17 are plotted the IRFs to a shock of the Effective Federal Funds rate for the sample 1992m7-2019m4. A shock in the federal funds increases the financial uncertainty, in line with the findings of Bekaert et Al. (2013) [12]²⁵. GFC decreases as a response to the monetary policy shock and overshoot shortly after eight months, as documented in Miranda-Agrippino Rey (2020) [62]. The CCF display a similar trend as the GFC, decreasing and increasing shortly after. CPI displays some rigidities in the first three months, to become negative shortly after and overshoot in the eighth month. Although interest rate shocks are well known for their deflationary effect on the economy, such effects do not stand out for the world industrial production and, partially, for the industrial production. WIP presents a positive trend, while INDPRO does not react strongly and stays in mild condition until the 16th month. This suggests that world output and industrial production responses can be due to the existence of the information channel argued in Hoesch et Al. (2020) [52].

3.2.4 VAR: Sub-sample analysis

In the following figures, we compute the impulse response functions over the sub-sample 2003m8-2019m4. As Introduced in Section 1.1, Hoesch et Al. (2020) [52] argued that in-

²⁵Bekaert et Al. (2013) found that the VIX, the stock market option-based implied volatility, strongly co-moves with measures of the monetary policy. They find that a lax monetary policy decreases the uncertainty measure, implying that an increase in interest rates should increase macroeconomic uncertainty.

formation channel weakened around mid-2000s. Running some tests, they agreed with the finding of Lunsford (2020) [60]; both found evidence of a structural break in August 2003. They argued that FOMC changed its communication strategy in that period and started including time-dependent forward guidance in its post-meeting statements. Therefore to identify a monetary policy shock, they computed IRFs of a proxy SVAR, considering that structural break. They found that IRFs for a monetary policy shock deliver correct results only if the monetary policy instrument is information-robust before August 2003. Keeping in mind that September 2003 also began the 2000s commodity boom, we are concerned about whether the SVAR estimated in a smaller sample delivers different IRFs, especially to a monetary policy shock.

Global Financial Uncertainty Shock In Figure 18 are plotted the impulse response function to financial uncertainty shock, computed over the sub-sample. Uncertainty shock computed over the sub-sample displays a similar, although not identical, the effect of the uncertainty shock computed over the full sample. GFC and CCF decrease on impact in the short run while WIP, CPI, INDPRO and interest rates fall over time. After one year, the uncertainty shocks have a less permanent effect on the variables than before; for instance: global financial factor, world output, Commodity factor and interest rates recover from the shock after twenty months and industrial production after two years. However, prices do not recover until the 33rd month.

Common Commodity Factor Shock Figure 19 reports the impulse response function to common commodity factor shock, computed over the sub-sample. With respect to the previous results, a commodity factor shock display more recessionary effects. WIP and GFC quietly increase in the first months to plunge after six months, then recover and stay and stay in mild negative conditions. The shock boosts American inflation and makes USA output fall over time. In the sixth month, as uncertainty spikes, CPI plunge down to recover a few months later. Interestingly, with respect to the IRFs computed on the previous sample, Fed responds immediately to the shock, lowering the interest rate over time.

Federal Funds Rate Shock In Figure 20 are plotted the impulse response function to an interest rate shock, computed over the sub-sample. The interest rate shock, in this case, displays a similar trend as before for the uncertainty, financial cycle, commodity

factor and prices(although with fewer rigidities). The variables decrease (increase for GFU) and become positive (negative) after eight months. Interestingly, world industrial production no longer shows a positive pattern in the first months, but it decreases and overshoots in the ninth month. Industrial production presents a trend similar to WIP.

3.2.5 VAR: Variance Decomposition

In this section, we investigate the quantitative significance of the shocks of interest for macroeconomic fluctuations in the two samples. To do so, we study the forecast error variance decomposition as explained in section 3.1.3 for all our macroeconomic variables. In each figure, the blue line represents the sample starting from august 2003 (2003 sample), and the grey line represents the sample starting from July 1992 (full sample).

Financial Uncertainty Shock Figure 21 are reported the FEVD of an uncertainty shock for the two samples. As we can see, the uncertainty seems to explain a large fraction of the forecasted variance in most of the variables. As already proven by Castelnuovo & Caggiano [17], explaining up to 45% at the 1-year horizon and, interestingly, at the 2-year horizon, the shock explains 38% of the GFC, for the 2003 sample, while the 47% for the full sample. The fraction of variance of the WIP explained by the GFU shock doubles, from a more or less 20% flat for all horizons to a 40% in the 2003 sample. Uncertainty shocks are also one of the main drivers of the commodity factor, explaining up to 24-22% at a 1-year horizon and 28% at a 2-year horizon. Interestingly FEVD of industrial production for the uncertainty shock dramatically increases in the 2003 sample, from a 10% flat for all horizons to a 52.78% at the 1-year horizon and 44.76% after two years. The share of interest rate variance explained by uncertainty shock is even more interesting. In the full sample, uncertainty explains 16.73% and 23.46% at one and 2-year horizons, respectively, while in the 2003 sample 4.48% and 3.1%.

Common Commodity Factor Shock In figure 22 are reported the FEVD of a Commodity factor shock for the two samples. The CCF shocks seem to explain a small fraction of the variance for all variables, but interesting insights exist. The fraction of GFU's variance explained by the commodity factor shock for the 2003 sample is about 12.48% and 12% at 1 and 2 years horizons, doubled with respect to the full sample. Interestingly, in the 2003 sample at a 1-year horizon, commodity factor shocks count for 14% of GFC variability, tripling with respect to the full sample. For the output variables, the CCF

shock explains a negligible portion of the variance. But it is interesting to notice that CCF becomes more significant for world industrial production in the 2003 sample. CCF shocks are relevant for the CPI variability, especially at one and two years horizons for the 2003 sample, explaining 16.17% and 13.05% respectively and decaying over time. The most intriguing finding is the effect on the federal funds rate. In the 2003 sample, the shock explains a large portion of the variability at all the horizons. For example, at one year, it explains about 20.24% increasing the share up to 29.57% at three years horizon. On the other hand, the full sample has a more mild path in the short horizon; the CCF shock contribution to the interest rate is about 3.79% at the year horizon, up to 22.57% at three years horizon.

Federal Funds Rate Shock In figure 23 are reported the FEVD of a federal funds rate shock for the two samples. Striking is the larger contribution of the shock on all variables for the 2003 sample with respect to the full sample. For example, for the two-year horizon, the contribution to financial uncertainty moves from 7.59% to 15.33%, and for the GFC moves from 5.99% to 11.3%. The FEVD of world output for an uncertainty shock dramatically increases in the 2003 sample with respect to the full sample, from a 7.28% for two years horizon to a 12.67%. Interestingly, the variability in the CCF is largely explained by the interest rate similarly in both samples; in the 2003 sample and full samples, the shock explains, respectively, 9.51% and 5.06% at the one-year horizon, while 18.89% and 16.98% at two years horizon. Interest rate shock in the 2003 sample explains 5.22% of the variability of industrial production at two years horizon, with respect to 0.22% of the full sample. Federal funds shock largely explain CPI. The contribution moves from 9.22% in the full sample to 20.57% in the 2003 sample at two years horizon.

3.3 Findings

In this section we draw the conclusions about our research, also giving some meaningful economic interpretations.

Finding 1. After August 2003, the information channel weakens, and a contractionary monetary policy shock leads to a more severe output reduction in the short run.

Our findings prove the results of Hoesch et al. (2021) [52]. As we said in section 1.1, Hoesch et al. (2021) [52] says that in the presence of the *information channel* agents infer

and learn about the future state of the world from the FOMC announcements, which has *information advantage*. Therefore in response to an increase in interest rate made to deflate output and prices, agents realize FED beliefs about output. Interestingly the CCF follow the movements of the GFC. A possible explanation is that the demand for commodities declines, especially in emerging countries, as the credit channel weakens, as Miranda & Rey (2020) [63] suggests. As this *information channel* exists, the response of inflation and industrial production to a monetary policy shock does not show an immediate strong declining trend. However, a more mild initial response, figure 17, especially for world output, which shows a positive trend since the beginning. In figure 20 the short-run responses to monetary policy shock for the three variables change drastically. The reason for such change in impulse responses is due to the strong weakening of the *information advantage* and the *information channel*, due to more overall transparency of the FED and implementation of forward guidance. Lunsford (2020) [60] claim that from August 2003 is fundamental date since the FOMC included *policy-inclination* forward guidance from a *economic-outlook* forward guidance. The addition of *policy-inclination* forward guidance in August 2003 changed how the private sector interpreted FOMC statements. From simply providing economic guidance to committing to future monetary stimulus, then information effects may have weakened, and standard effects may have been more relevant from August 2003²⁶. Claiming also that forward guidance that stresses on economic outlook risks causes tougher information effects than forward guidance that emphasizes policy inclinations. A consideration of our findings has to be made. Our impulse responses are computed on two different samples. Therefore the difference in results can be attributed solely to the sample used. In our defense, our impulse responses show similar shapes at certain horizons, and a similar conclusion can be drawn. Therefore we can claim that the samples used are roughly similar.

Finding 2. After August 2003, an Uncertainty shock plays a much smaller role in explaining the interest rates adopted by the FED but a more relevant role on output variables.

A large share of literature addresses uncertainty shock most of the business cycle fluctuations. As our results prove, a shock of this kind leads to a contraction in real

²⁶The results of the findings of Lunsford (2020) [60] are referred to the period he took into consideration, 2000m2-2006m5

activity via "real option" effects²⁷, which affect investment, and precautionary savings effects, which influence consumption if agents are risk-averse. Policymaker, to offset these recessionary effects, tends to lower interest rates, figures 15 and 18. Although, as also shown by Caggiano et al. (2017) [19], these effects hit different when we are close to zero lower bound (ZLB). Our sample starts from August 2003, and we know that between December 2008 to December 2015, the interest rates remain at the ZLB. Consequently, since the interest rate cannot move and offset the effect of uncertainty, and (Uncertainty) shock displays more recessionary consequences. Although Caggiano et al. (2017) [19] found that IRFs to the shock have much stronger recessionary effects, our results do not display particular differences between the two samples. On the other hand, we can tell that financial uncertainty shocks in the presence of many years of ZLB explain a much larger fraction of the variance of world and USA output. Of course, since the interest rate does not move in response to the uncertainty shock, the fraction explained is negligible.

Finding 3. Independently from the sample used, the financial uncertainty shocks contribute to a large fraction of the volatility of the commodity factor. Moreover, the shock has a recessionary effect on the variable.

As we argued in section 2.2.1, our common commodity factor follows the business cycle. Therefore, in a recession period, the factor displays negative trends and vice-versa during expansion periods. The shock's large negative impact and large variance contribution can be explained by the uncertainty that arises on future production, governance, or finance. For example, Erten et al. (2013) [42] argue that the choice to expand capacity through new capital expenditures is closely connected to current pricing levels in relation to anticipated future trends. Davis & Samis (2006) [35] say It takes up to twenty years for capital to be invested in a project in the mining sector for revenues to be realized. Therefore, private and state-owned businesses must consider such patterns when making investment decisions. Most importantly, as said earlier, financial investors are using commodities as an instrument to diversify their portfolio to hedge against unexpected risks; Uncertainty about the economy's future path and the future path of the business cycle can explain a big part of the fluctuations in commodity factor.

²⁷When an investment is irreversible, the real options effect of uncertainty is defined as "the effect of uncertainty that derives from a firm's choice to pick the timing of its investment.", Bloom (2001) [16].

Finding 4. Commodity Factor shock leads to an increase in world economic and financial activity in the short run, but a recession after.

One of the most interesting findings are the results in figures 16 and 19. The IRFs of both samples for GFC, WIP, and GFU display a similar trend to CCF shock. First, we see a small increase in financial and economic activity in the short-run (seven months), then an increase in uncertainty which is followed by a drop in industrial production and financial cycle. We believe that global demand for commodities is associated with a period of overall wealth. Therefore, we provide two possible explanations. First, according to Killian & Park (2009), unanticipated shifts in global demand for inputs associated with the business cycle increase economic activity and stock returns; the stimulating effects dominate in the short-run, and financial and business cycles thrive despite the price increase; after one year the path reverses. Second, according to Reinhart (2009) [69], during a period of economic stability, the investor looks for opportunities abroad, i.e. emerging economies, leading to large capital flow into countries. During these periods of capital flow, bonanza commodity prices rise worldwide, and asset prices and exchange rates appreciate. Even though capital inflows are a good thing, this often leads to exacerbation of the country's structural weaknesses. Moreover, policymaker in EMEs tends to treat these capital flows as permanent, exploiting the period of bonanza to give more fiscal stimulus and obtain electoral consensus. After fiscal balances are exacerbated, and capitals stop flowing in (*sudden stop*)²⁸.

Finding 5. Commodity Factor shock increase CPI and decrease industrial production and interest rates over time. Moreover, the commodity factor shock seems to explain a big part of the variability in the Federal funds rate. This is true, especially after August 2003.

The Commodity factor shock does not affect all countries in the same way. The different responses between global output and US production prove the story that movements in commodities prices are mostly driven by expansion in emerging markets. These unanticipated shifts in demand shift prices upward, leading the US (developed economies) into stagflation. Interesting is the interest rate response that decreases over time to offset the recession. A big share of the variability in the sub-sample in the Federal funds rate

²⁸Reinhart (2009) also saw that the probability of default after a capital flow bonanza is about 60% in EMEs, lower in developed countries.

is explained by the CCF (28% at the 2-year horizon). This suggests that commodities demand affects the responses in the FED policy through prices²⁹. Common Taylor's rule knowledge suggests that an unanticipated increase in prices should lead to an increase in interest rate, though, under stagflation, the correct response is debatable.

Finding 6 Uncertainty shocks are the main driver of business and financial activity at all years' horizons.

In table 6 we report the forecast error variance decomposition of GFC and WIP for each of the shocks of interest. Independently from the sample used, the Uncertainty shocks appear to be the main driver of the global financial cycle and industrial production. In the full sample, the contribution to GFC of uncertainty shocks is around 46,17% at two years horizon, slightly lower in the sub-sample (38.35%). As said in finding 2, the contribution of uncertainty to world industrial production is higher as the sub-sample comprehends long periods of ZLB of interest rate, the inability of FEDs to lower the interest rate and to offset the effect of uncertainty leads to a higher contribution of uncertainty shock to industrial production. In the sub-sample, the CCF and monetary policy shocks contribute more than monetary policy shocks to fluctuations in GFC (14% and 6.6% respectively). However, they contribute equally over a two years horizon. CCF shocks are far less relevant than federal funds rate shocks to fluctuations in WIP (5.69% and 12.67% at two years horizon). The overall results confirm the finding of Caggiano and Castelnuovo (2021) [17], that address uncertainty as to the main driver of the global financial cycle and real activity.

²⁹Balke & Emery (1994) [6] claim that commodity prices provide information about future inflation; therefore, the commodity should be inserted into the reaction function of the central bank. Similarly, our factor can be considered as an observable demand for commodities for the central bank. Its exogenous shock triggers a response of the FED to offset increasing inflation deriving from upward pressure for commodities. This is in line with the feedback rule of Taylor (1993) [73], as intended in Christiano et al. (1994) [31] and Balke & Emery (1994) [6]. In addition, According to Christiano et al. (1994) [31] and Balke & Emery (1994) [6], including commodity price to VAR equation with a recursive identification solve the price puzzle, leading to a more severe impact of an interest rate shock on the IRFs of prices and output. In the absence of commodity prices, a monetary policy shock leads to an increase in inflation, conversely from what the common DGSE model suggests.

4 Conclusions

This thesis aims to study the importance of uncertainty, commodity prices and FED's monetary policy shocks on the global financial and economic cycles. First, we propose a novel measure of commodity price index. We extract the common commodity factor (CCF) via a dynamic factor model (DFM) à la Delle Chiaie (2017) [37] from a large IMF dataset of commodity prices. The CCF shows a high correlation with the CPB world trade measure (0.846), confirming that it represents the global demand for commodities associated with the business cycle. Second, we estimate a seven-variable VAR model, i.e. our CCF, the global financial factor (GFC) proposed by Rey & Miranda-Agrippino (2020) [62], global financial uncertainty (GFU) estimated by Caggiano & Castelnuovo (2021) [17], World production (WIP) proposed by Baumasiter and Hamilton (2019) [9], U.S. industrial production, consumer price index and federal funds rate. Then, through a recursive (Cholesky) identification, we compute the impulse response functions (IRFs) to analyze the dynamic consequences of an unanticipated shift in our variables of interest and the forecast error variance decomposition (FEVD) to understand the relative contribution of each shock to other variables fluctuations. From a first analysis, we obtained deceiving results from monetary policy shocks, i.e. increase in output as a response to a contractionary monetary policy. An explanation for this problem is provided by Hoesch et al. (2020) [52], arguing that a monetary policy shock may be dominated by an information shock when the central bank has an information advantage with respect to market participants. We re-run our VAR-analysis on a sub-sample that starts from August 2003, as Lunsford (2020) [60] argues that in that month, FED changed its communication strategy. The IRFs to the shock of monetary policy we retrieve from the sub-sample are in line with the common DGSE model; this suggests that the *information channel* weakens as Hoesch et al. (2020) predicted. Our results confirm the worldwide recessionary effect of US monetary policy, argued in Miranda-Agrippino & Rey (2020) [63]. A shock in global demand for the commodity (CCF) is associated with an increase in WIP and GFC in the short-run and a recession shortly after. We suggest that an increase in worldwide commodity demand is associated with a capital flow bonanza in emerging countries, as suggested in Reinhart (2009) [69]. This bonanza of capital forces the industrialization period and wealth in EMEs countries but eventually exacerbates their structural weaknesses, often leading to sovereign default episodes. Finally, we confirm the findings of Caggiano and Castelnuovo (2021) [17]; financial uncertainty shocks lead to grave worldwide recessionary

effect, and we address it as the main driver of GFC and WIP.

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Tables and figures

Table 1: Database structure

Global	Blocks	Sub-blocks	Groups	N°Series
All Commodities (PALLFNF) 100.0				68
	Fuel (PNRG) 40.9			9
			Oil (POILAPSP) 28.6	3
			Natural Gas (PNGAS) 7.8	3
			Coal (PCOAL) 3.0	2
	Non-Fuel (PNFUEL) 59.1			59
		Food & Bevarages (PFANDB) 29.9		33
			Food (PFOOD) 27.7	29
			Bevarages (PBEVE) 2.2	4
		Industrial Inputs (PINDU) 27.2		23
			Agricultural Raw Materials (PRAWN) 4.4	9
			Metals (PMETA) 11.3	10
			Precious Metals (PPMETA) 11.5	4
		Fertilizers (PFERT) 2.0		3

Table 2: Data labels and weights

Mnemonic	Unit	Label	IMF global commodity index 2014-2016 weights
PALLFNF	Index	All Index	100.0
PNRG	Index	Fuel Index	40.9
PNFUEL	Index	Non-Fuel Index	59.1
POILAPSP	Index	Crude-Oil Index	28.6
PNGAS	Index	Natural Gas Index	7.8
PCOAL	Index	Coal Index	3.0
PINDU	Index	Industrial Input Index	27.2
PRAWM	Index	Agricultural Raw Material Index	4.4
PMETA	Index	Base Metals Index	11.3
PPMETA	Index	Precious Metals Index	11.5
PFERT	Index	Fertilizers Index	2.0
PFANDB	Index	Food&Beverage Index	29.9
PFOOD	Index	Food Index	27.7
PBEVE	Index	Beverage Index	2.2
POILWTI	USD	WTI Crude	9.5
POILDUB	USD	Dubai Crude	9.5
POILBRE	USD	Brent Crude	9.5
PNGASJP	USD	LNG, Asia	2.6
PNGASEU	USD	Natural gas, EU	2.6
PNGASUS	USD	Natural Gas, US Henry Hub Gas	2.6
PPROPANE	USD	Propane	1.5
PCOALAU	USD	Coal, Australia	1.5
PCOALSA	USD	Coal, South Africa	1.5

Continued on next page

Table 2 – *Continued from previous page*

Mnemonic	Unit	Label	IMF global commodity index 2014-2016 weights
PALUM	USD	Aluminum	1.6
PCOBA	USD	Cobalt	0.1
PCOPP	USD	Copper	3.4
PIORECR	USD	Iron Ore	3.4
PLEAD	USD	Lead	0.4
PLMMODY	USD	Molybdenum	0.6
PNICK	USD	Nickel	0.7
PTIN	USD	Tin	0.2
PURAN	USD	Uranium	0.4
PZINC	USD	Zinc	0.6
PCOTTIND	USD	Cotton	0.8
PHIDE	USD	Hides	0.2
PRUBB	USD	Rubber	0.8
PLOGSK	USD	Hard Logs, Import Price Japan	0.3
PSAWMAL	USD	Hard Sawnwood, Dark Red Meranti	0.7
PLOGORE	USD	Soft Logs	0.3
PSAWORE	USD	Soft Sawnwood, Average of Softwoods	0.9
PWOOLC	USD	Wool, Coarse	0.2
PWOOLF	USD	Wool, Fine	0.2
PGOLD	USD	Gold	10.1
PPALLA	USD	Palladium	0.3
PPLAT	USD	Platinum	0.4
PSILVER	USD	Silver	0.7

Continued on next page

Table 2 – *Continued from previous page*

Mnemonic	Unit	Label	IMF global commodity index 2014-2016 weights
PDAP	USD	Diammonium phosphate	0.5
PPOTASH	USD	Potassium Fertilizer	0.6
PUREA	USD	Urea	0.9
PCOFFOTM	USD	Coffee, Other Mild Arabica	0.7
PCOFFROB	USD	Coffee, Robustas	0.7
PCOCO	USD	Cocoa	0.6
PTEA	USD	Tea, Kenyan	0.2
PBARL	USD	Barley	0.2
PMAIZMT	USD	Corn	1.1
POATS	USD	Oats	0.1
PRICENPQ	USD	Rice, Thailand	0.6
PSORG	USD	Sorghum	0.1
PWHEAMT	USD	Wheat	1.4
PBEEF	USD	Beef	2.1
PLAMB	USD	Lamb	0.3
PPOULT	USD	Poultry	1.0
PPORK	USD	Swine	1.5
POLVOIL	USD	Olive Oil	0.3
PPOIL	USD	Palm Oil	1.1
PROIL	USD	Rapeseed Oil	0.9
PSMEA	USD	Soybean Meal	0.8
PSOYB	USD	Soybeans	1.8
PSOIL	USD	Soybeans Oil	0.3

Continued on next page

Table 2 – *Continued from previous page*

Mnemonic	Unit	Label	IMF global commodity index 2014-2016 weights
PSUNO	USD	Sunflower Oil	0.4
PSALM	USD	Fish	2.5
PSHRI	USD	Shrimp	1.4
PSUGAISA	USD	Sugar, No. 11, World	1.4
PSUGAUSA	USD	Sugar, No. 16, US	0.2
PAPPLE	USD	Non-Citrus Fruit, Apple	1.2
PBANSOP	USD	Bananas	0.9
PFSHMEAL	USD	Fish Meal	0.1
PCHANA	USD	Legumes, Chickpea	0.4
PMILK	USD	Dairy Products, Milk	0.9
PGNUTS	USD	Groundnuts	1.0
PORANG	USD	Orange	1.1
PTOMATO	USD	Vegetables, Tomato	2.8

Table 3: Correlation between gold and other selected commodities

	POILBRE	PUREA	PWHEAMT	PCOCO	PCOTTIND	PCOPP	PGOLD
POILBRE	1						
PUREA	0.852	1					
PWHEAMT	0.783	0.793	1				
PCOCO	0.719	0.638	0.607	1			
PCOTTIND	0.477	0.449	0.552	0.453	1		
PCOPP	0.890	0.814	0.776	0.753	0.555	1	
PGOLD	0.747	0.68	0.643	0.781	0.504	0.867	1

Table 4: Correlation in precious metal group

	PGOLD	PPALLA	PPLAT	PSILVER
PGOLD	1			
PPALLA	0.754	1		
PPLAT	0.729	0.325	1	
PSILVER	0.927	0.5820	0.847	1

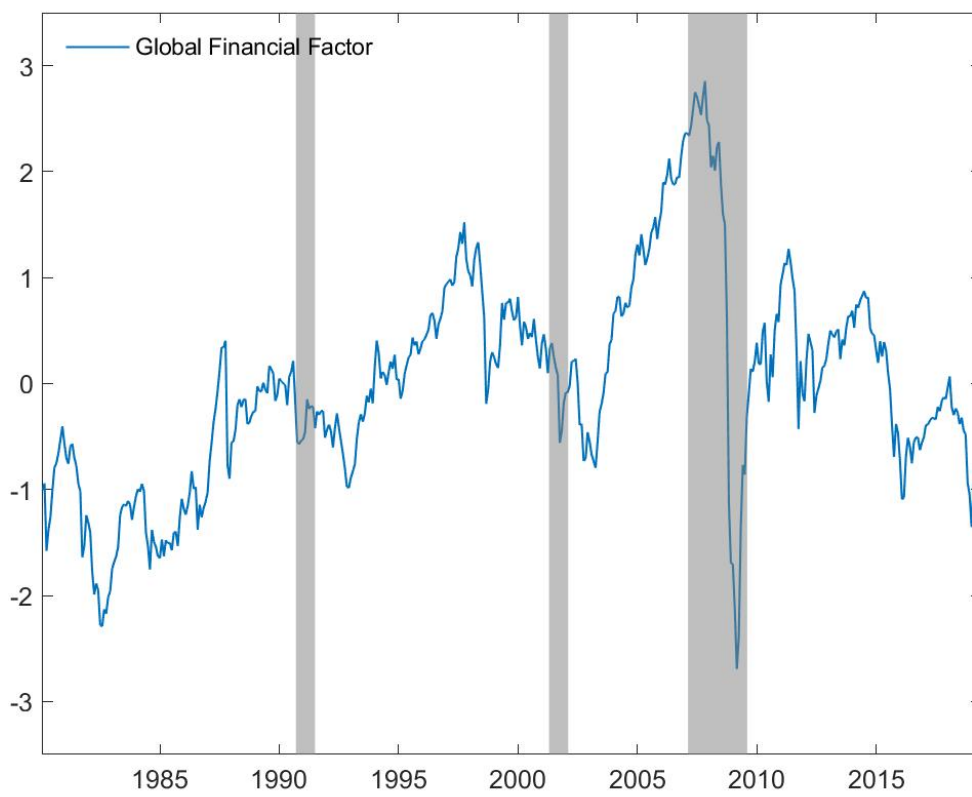
Table 5: VAR dataset

Label	Description	Source	Transformation
GFU	Global Financial Uncertainty	Caggiano & Castelnuovo (2021) [17]	//
GFC	Global Financial Cycle	Miranda-Agrippino, Nenova & Rey (2020) [61]	//
WIP	World Industrial Production	Baumeister & Hamilton (2019) [9]	100log
CCF	Common Commodity Factor	As in Figure 5	//
INDPRO	USA Industrial Production	FRED-MD	100log
CPIACSL	Consumer Price Index for All Urban Consumers: All Items in U.S. City Average	FRED-MD	100log
FF	Federal Funds Rate	FRED-MD	//
SR	Shadow Rate	JC Wu, FD Xia (2016) [75]	//

Table 6: Variance Decomposition of GFC and WIP

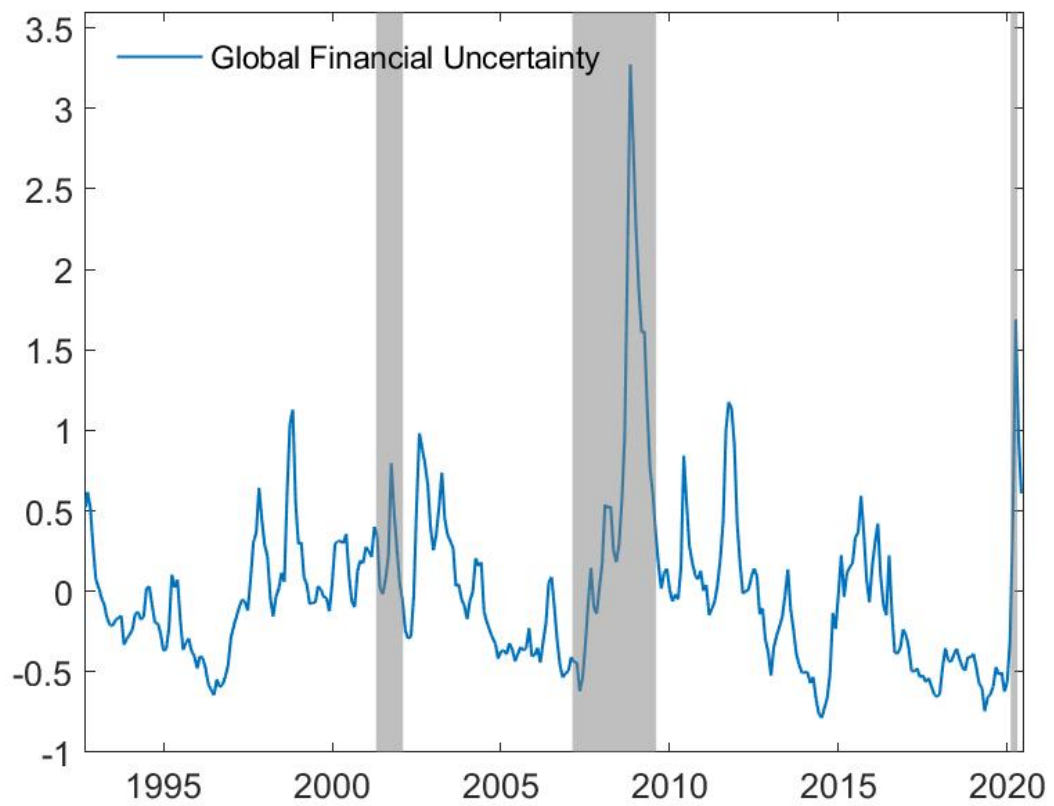
Sample	Variable	Shock	1 year	2 years	3 years	4 years
Full Sample	GFC	GFU	46.6	47.16	47.36	45.33
		CCF	4.18	4.4	4.28	4.09
		FF	2.3	6	6.02	6.45
	WIP	GFU	20.74	27.52	28.68	27.53
		CCF	1.69	1.79	1.71	1.7
		FF	2.71	7.29	7.08	6.95
Sub- Sample	GFC	GFU	45.93	38.35	39.68	38.64
		CCF	14	11.74	11.56	11.27
		FF	6.6	11.21	10.68	11.27
	WIP	GFU	45.99	46.64	46.04	43.78
		CCF	6.17	5.69	5.26	5.34
		FF	3.63	12.67	10.92	12.88

Figure 1: Global Financial Factor



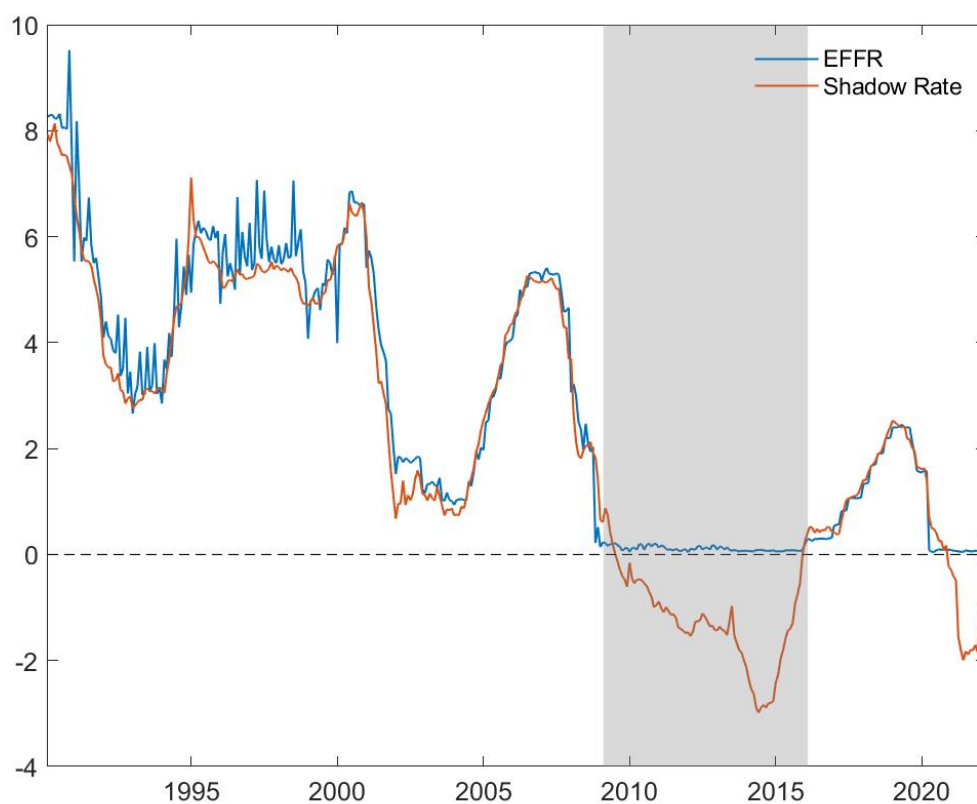
Note: The Figure shows the global financial factor estimated by Miranda-Agrippino, Nenova & Rey (2020) [62]. The grey area refers to period of widespread recession.

Figure 2: Global Financial Uncertainty



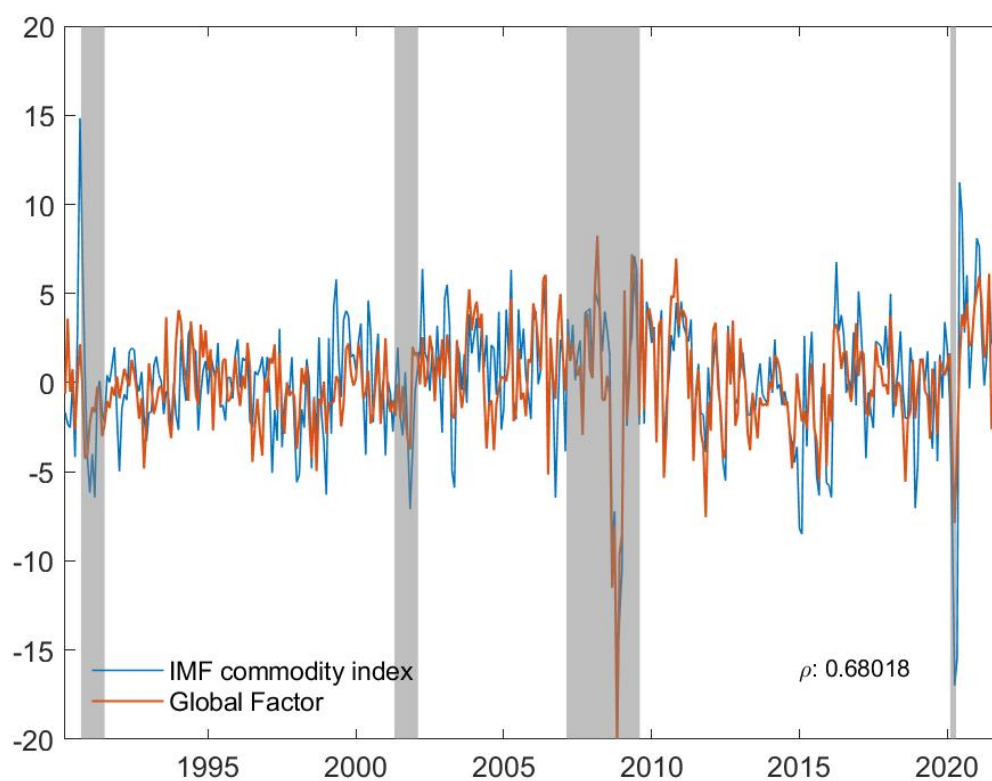
Note: The Figure shows the global financial factor estimated by Caggino & Castelnovo (2021) [17]. The grey area refers to period of widespread recession.

Figure 3: Effective Federal Funds rate and Shadow rate



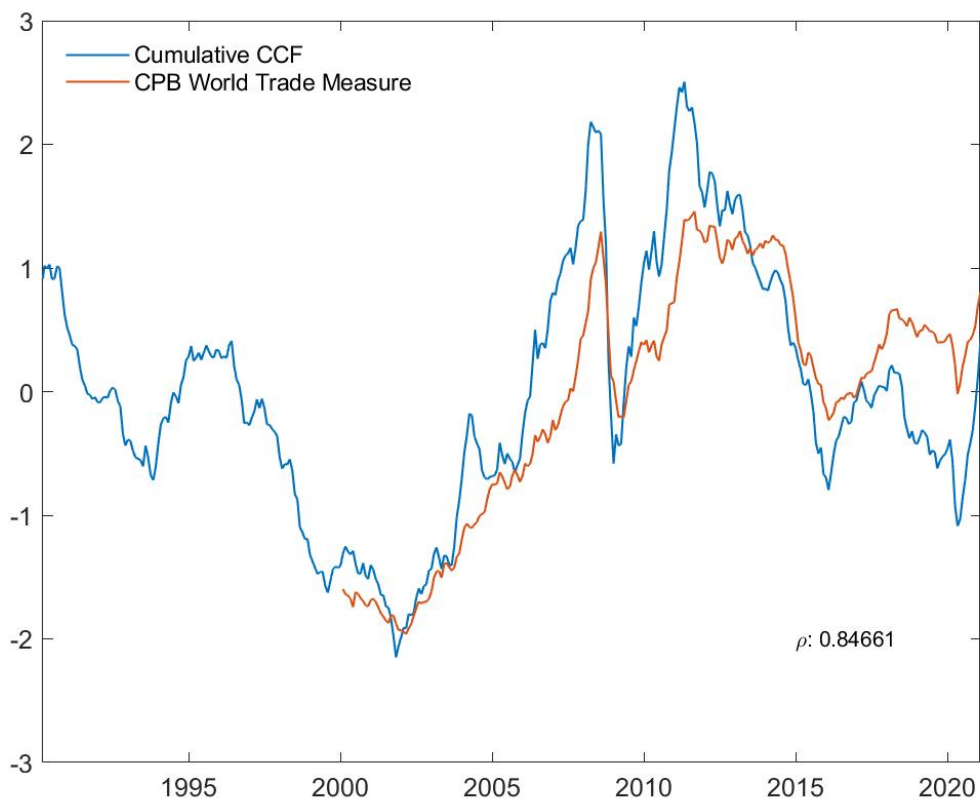
Note: The Figure shows the effective federal funds rate (blue line) along with the shadow rate (orange line) of Wu & Xia (2016) [75]. The grey area refers to the period 2008m12-2015m12.

Figure 4: The common commodity factor



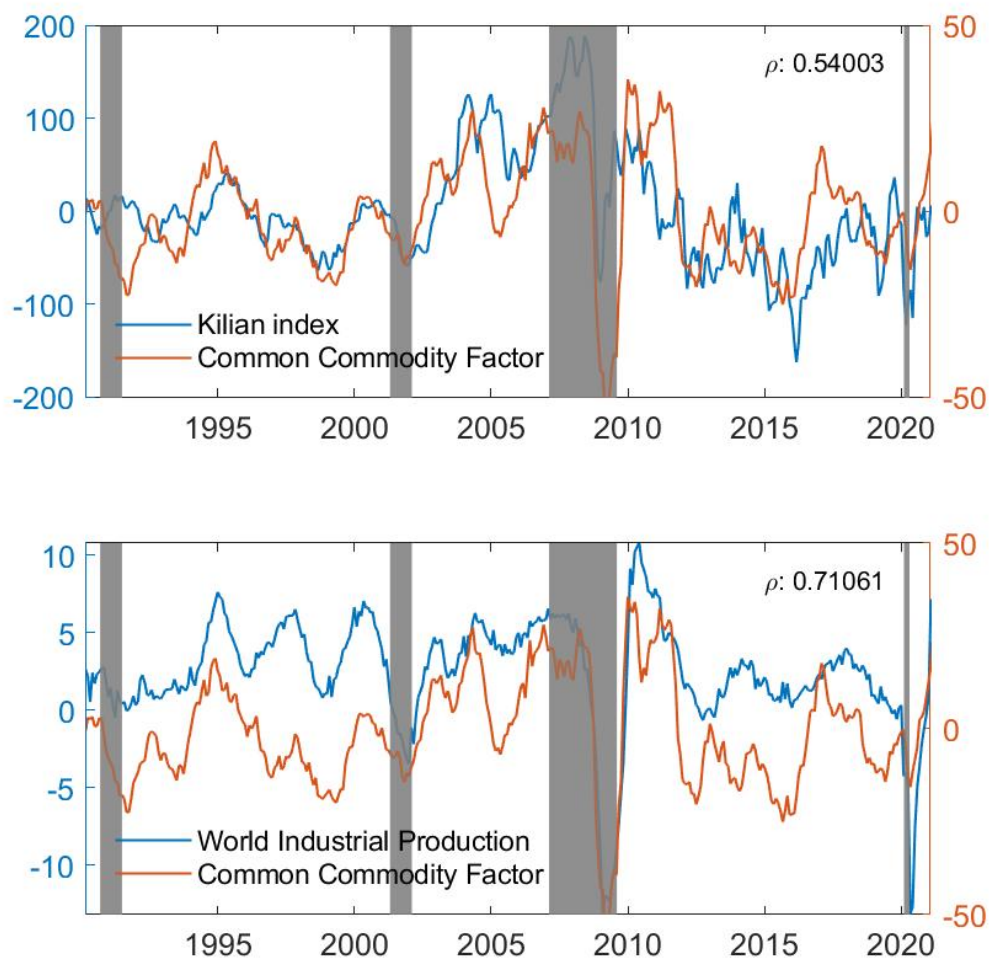
Note: The Figure shows the estimated Global Factor (Orange line) and the IMF overall index of commodity prices (Blue line). The vertical bars represent periods of widespread economic recession.

Figure 5: Cumulative common commodity factor



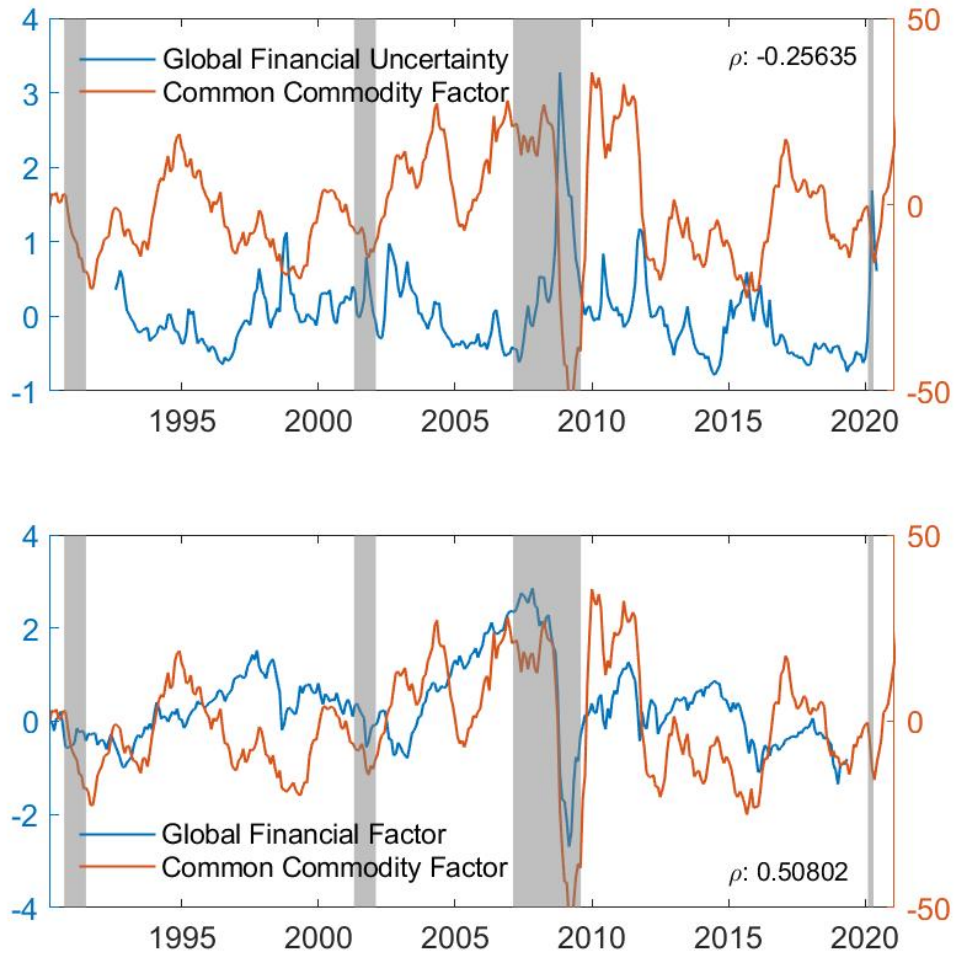
Note: The Figure shows the cumulative global commodity factor along with CPB measure of world trade. Both series have been normalized

Figure 6: The CCF and other measures of global economic activity.



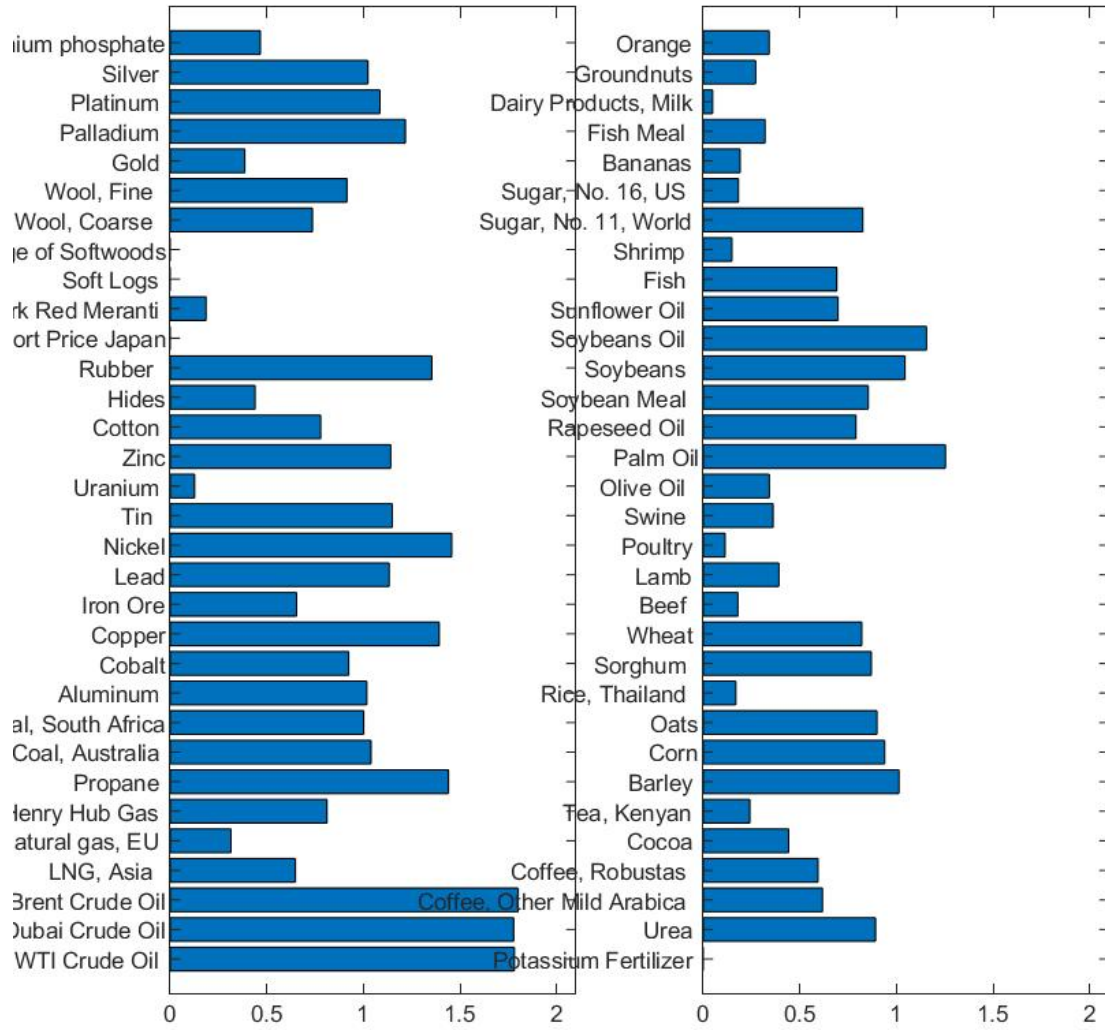
Note: all variables are expressed as year-on-year growth rate. In the top figure there is the CCF (orange line) and the Kilian's (2009) [57] index of real economic activity (blue line). In the bottom figure there is the CCF (orange line) and the Baumaister and Hamilton (2019) [9] world industrial production (blue line).

Figure 7: The CCF, GFC, GFU.



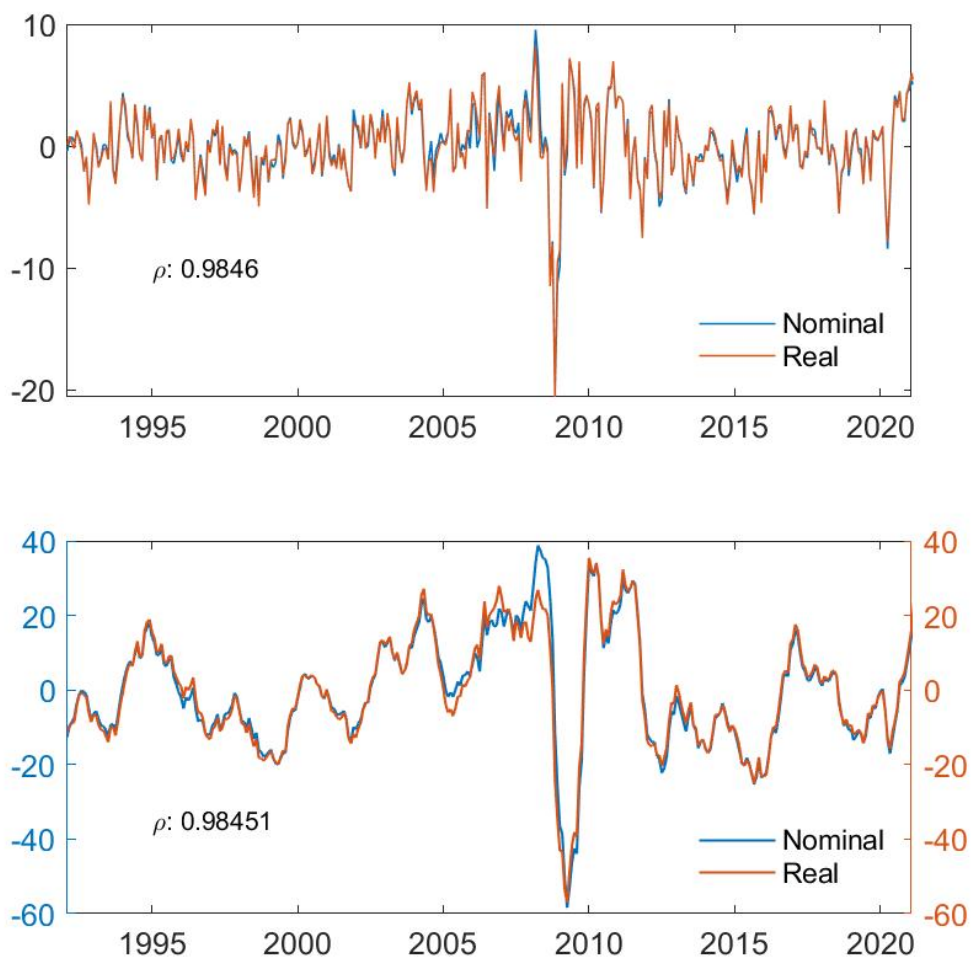
Note: The CCF is expressed as year-on-year growth rate. In the top figure there is the CCF (orange line) and the Caggiano, Castelnuovo (2021) [20] factor of financial uncertainty (blue line). In the bottom figure there is the CCF (orange line) and the Miranda-Agrrippino, Rey (2014) [64] factor of financial activity (blue line).

Figure 8: Factor loadings



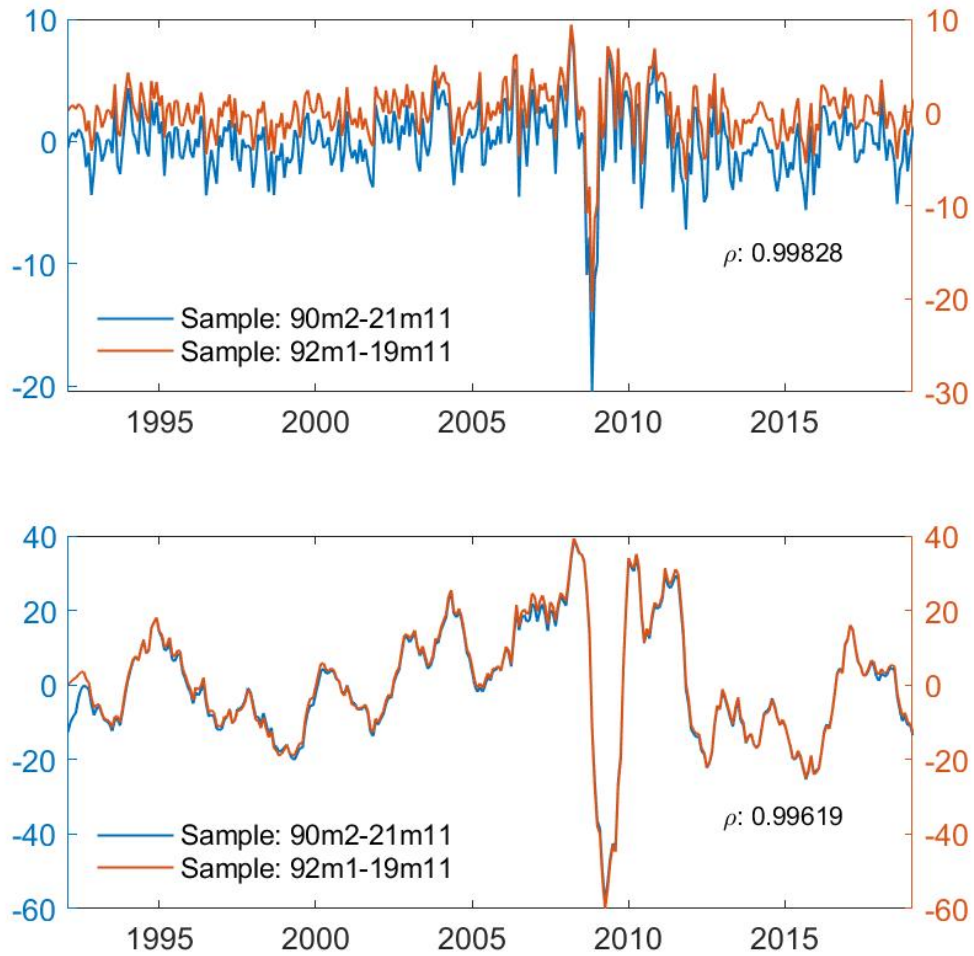
Note: Loading associated with the Common Commodity Factor.

Figure 9: The CCF extracted from real commodity prices



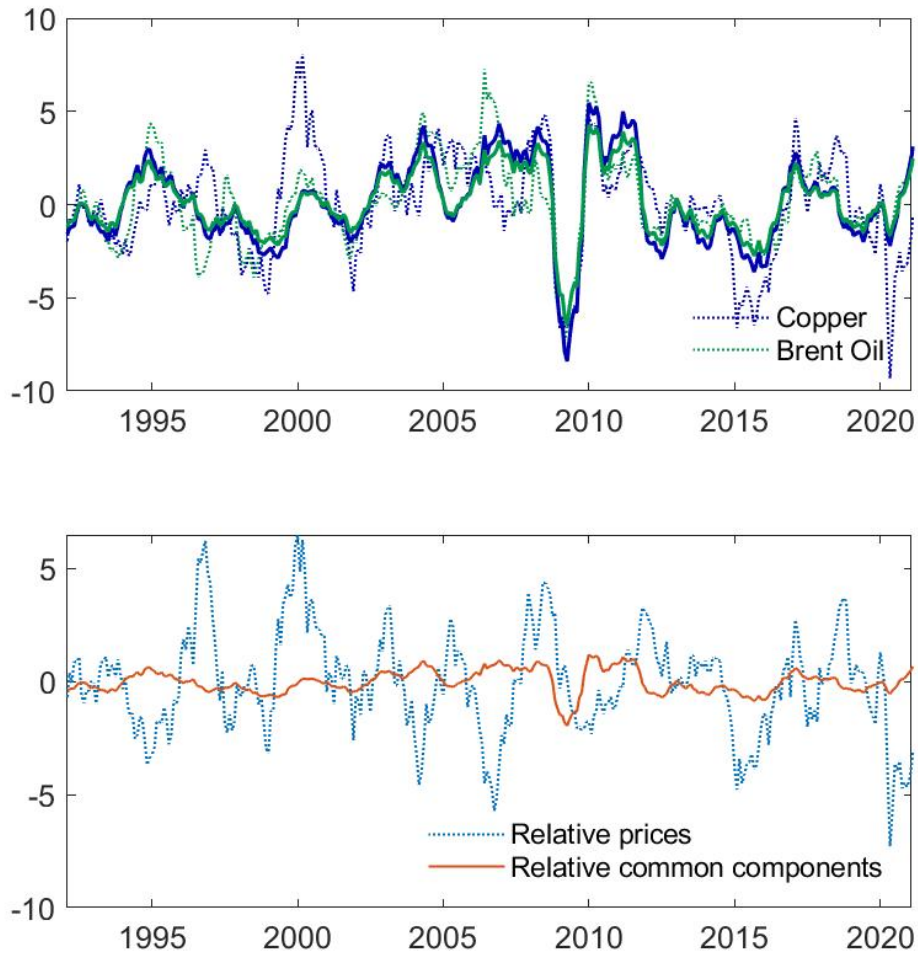
Note: Top figure reports the common factor extracted from real price series. Bottom figure reports the nominal and real common factor expressed in year-on-year growth rates. Correlation on screen

Figure 10: The CCF extracted from different sample.



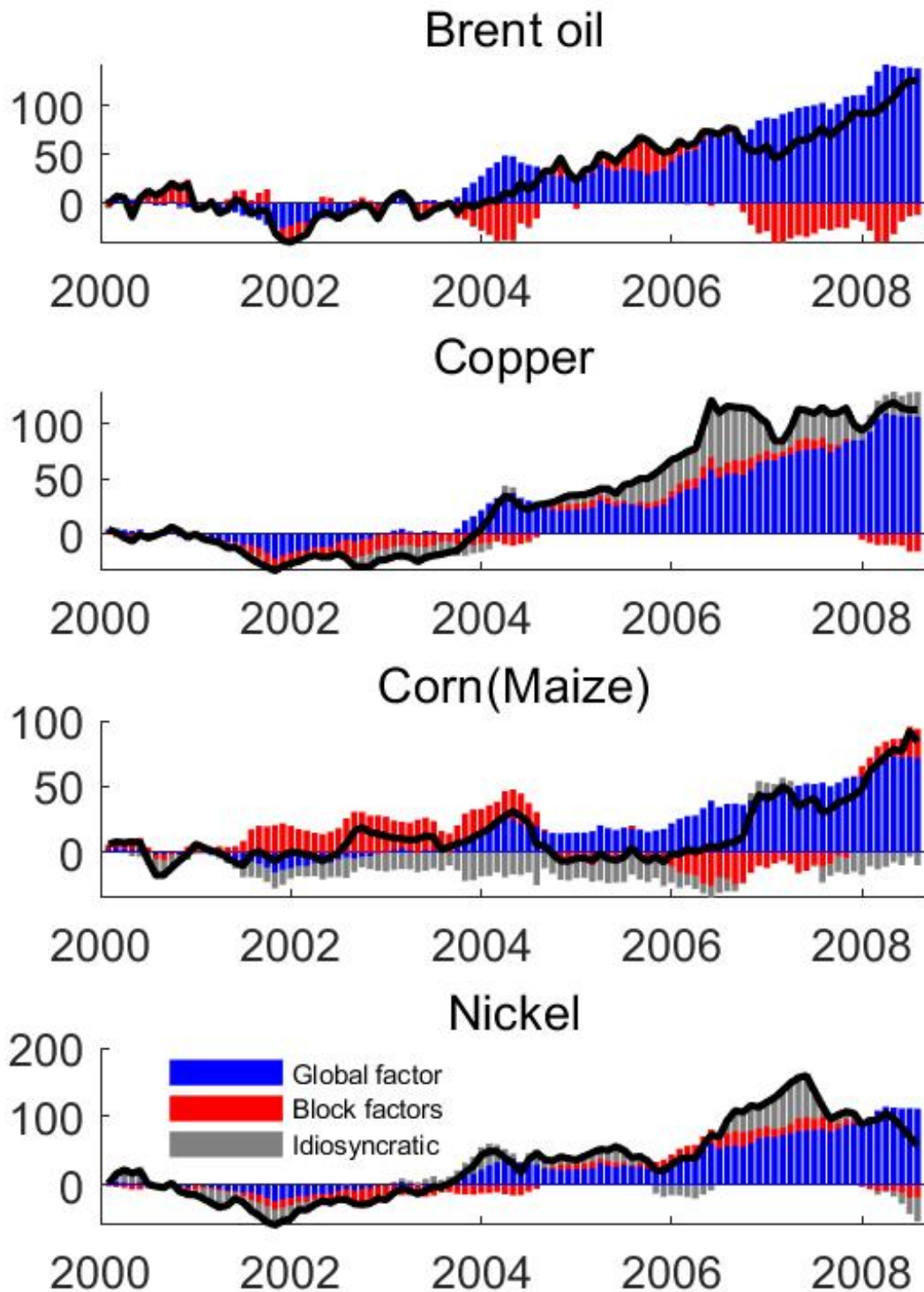
Note: Top figure reports the common factor extracted from a smaller sample series (1992m1-19m11) (orange line) and the original sample (blue line). Bottom figure reports the two factors expressed as year-on-year growth rates.

Figure 11: CCF and variations in relative prices



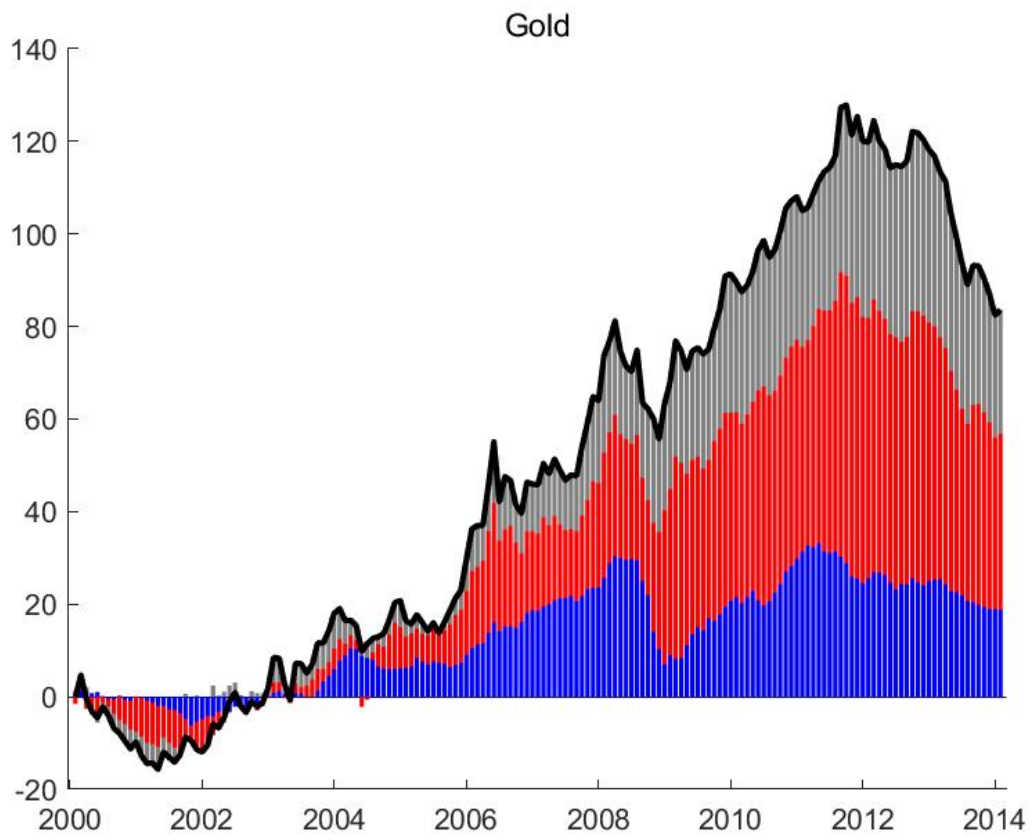
Note: Solid lines in the top figure express the brent oil and copper price series fitted with the common factor expressed as year-on-year growth rate, while the dotted lines represents the year-on-year growth rate of Brent crude oil and Copper. Bottom panel represents the relative prices.

Figure 12: Historical decomposition



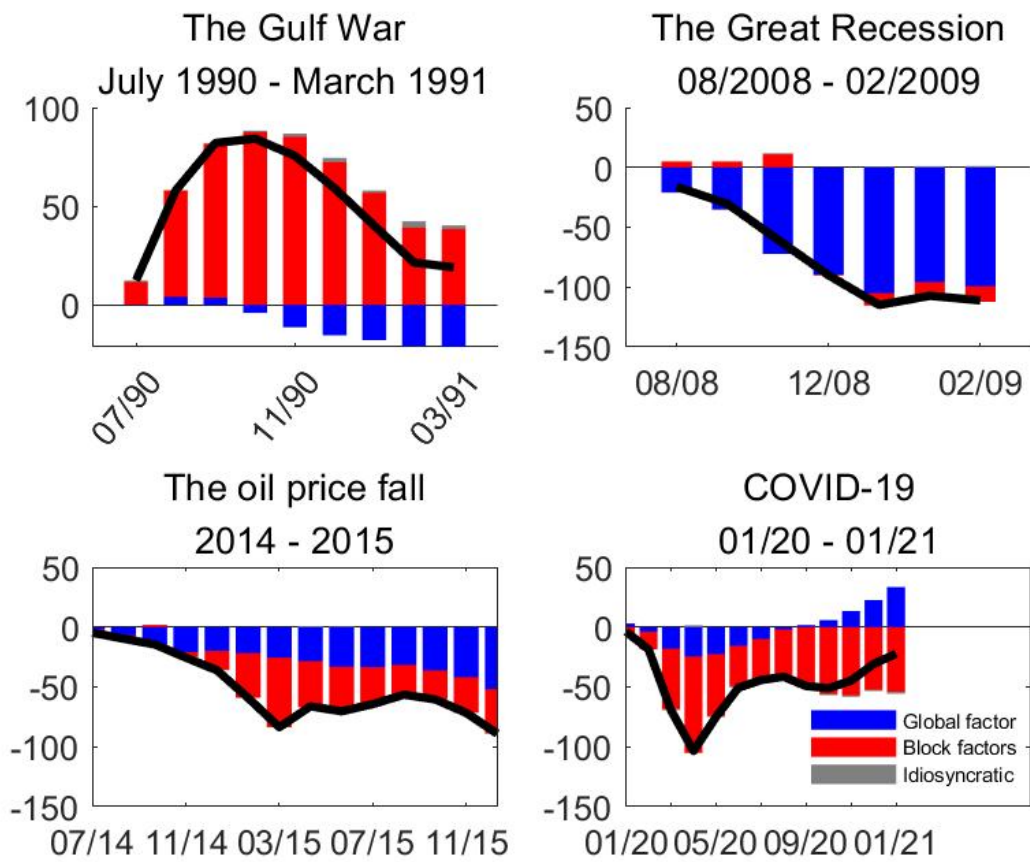
Note: Historical decomposition of four commodities for the period of 2000m1-2008m7.

Figure 13: Historical decomposition of gold



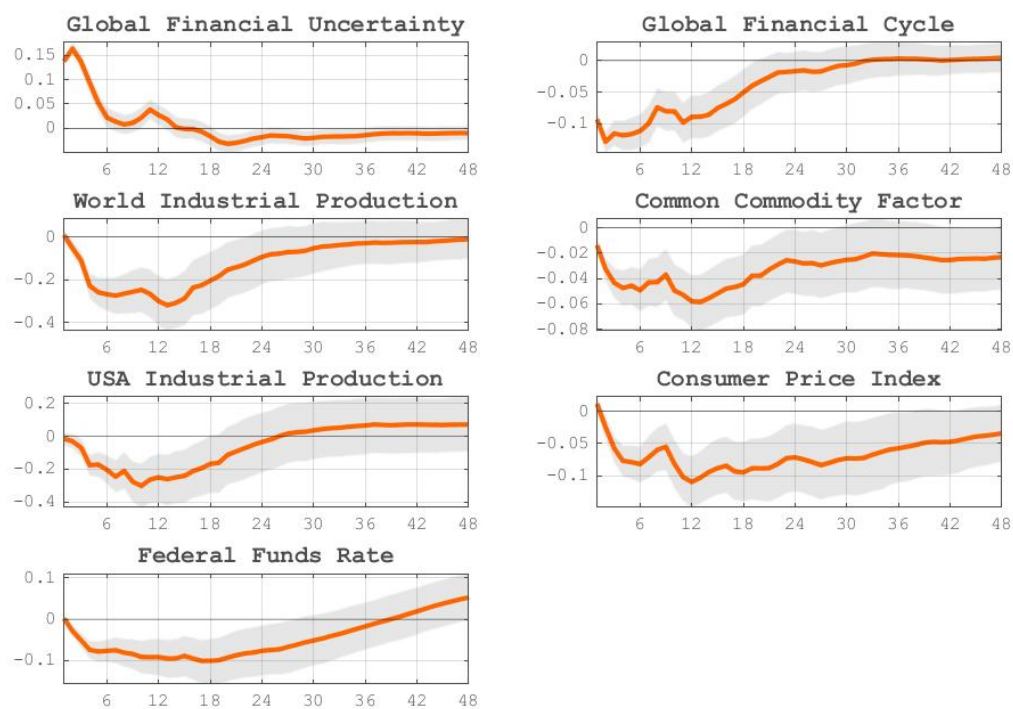
Note: Historical decomposition of Gold for the period 2000-2014.

Figure 14: Oil prices cases



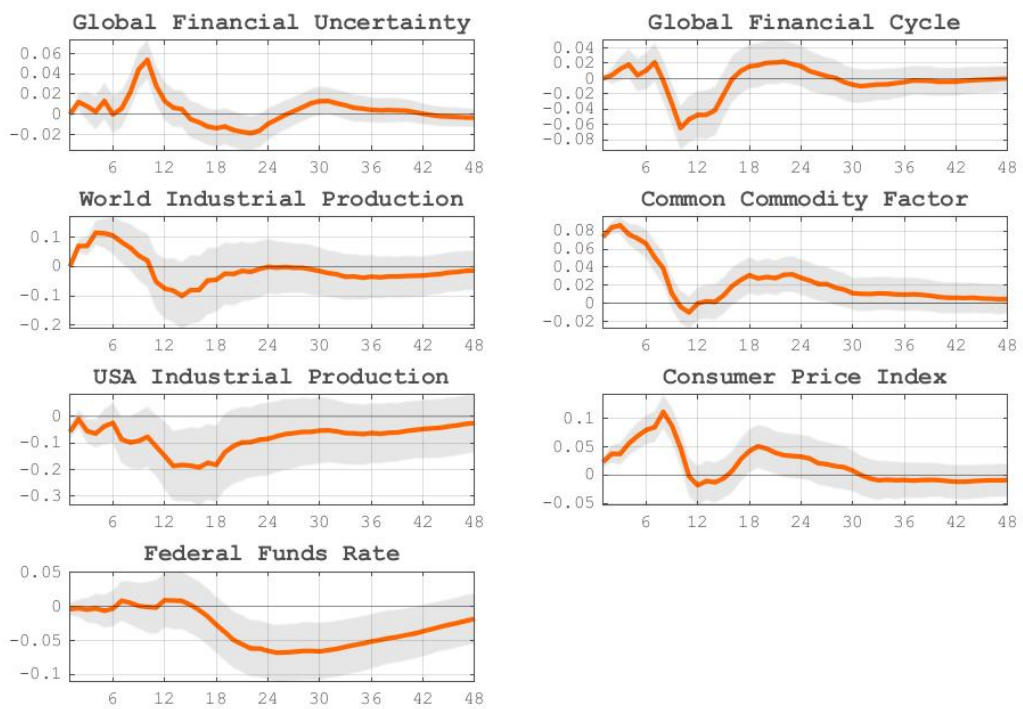
Note: Historical decomposition of oil prices for selected time period.

Figure 15: Impulse response functions to GFU shocks, sample: 92m7-19m4



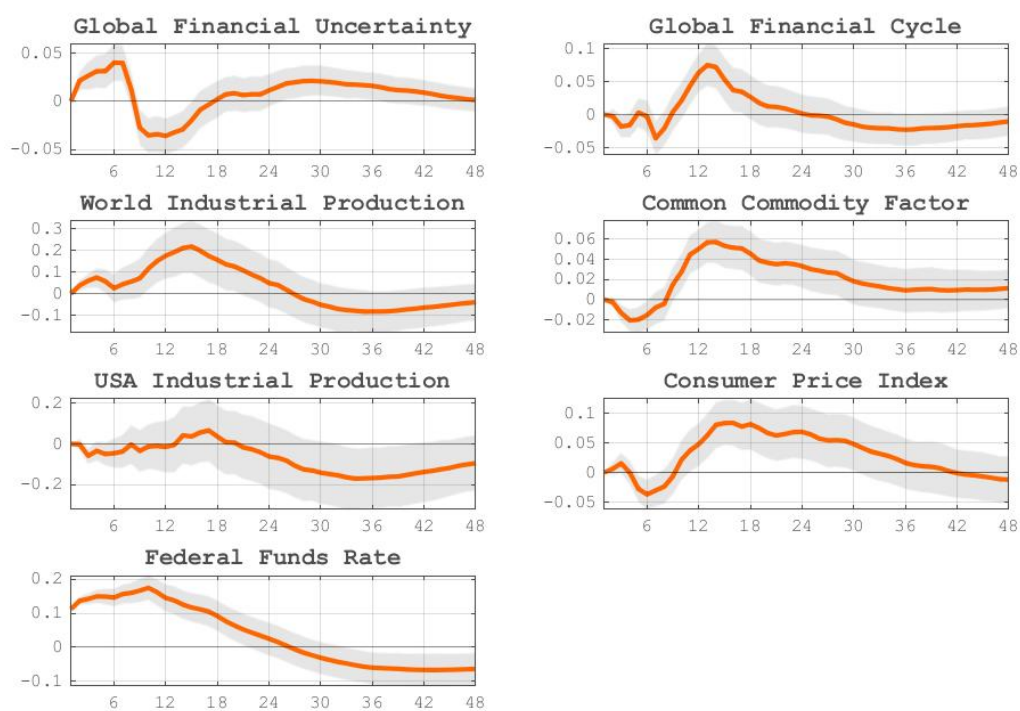
Note: Impulse response function to shock of Global financial Uncertainty factor of Caggiano, Castelnuovo (2021) [20]. Estimation sample: 1992m7 - 2019m4. Shaded regions represent the 68% confidence intervals.

Figure 16: Impulse response functions to CCF shock, sample: 92m7-19m4



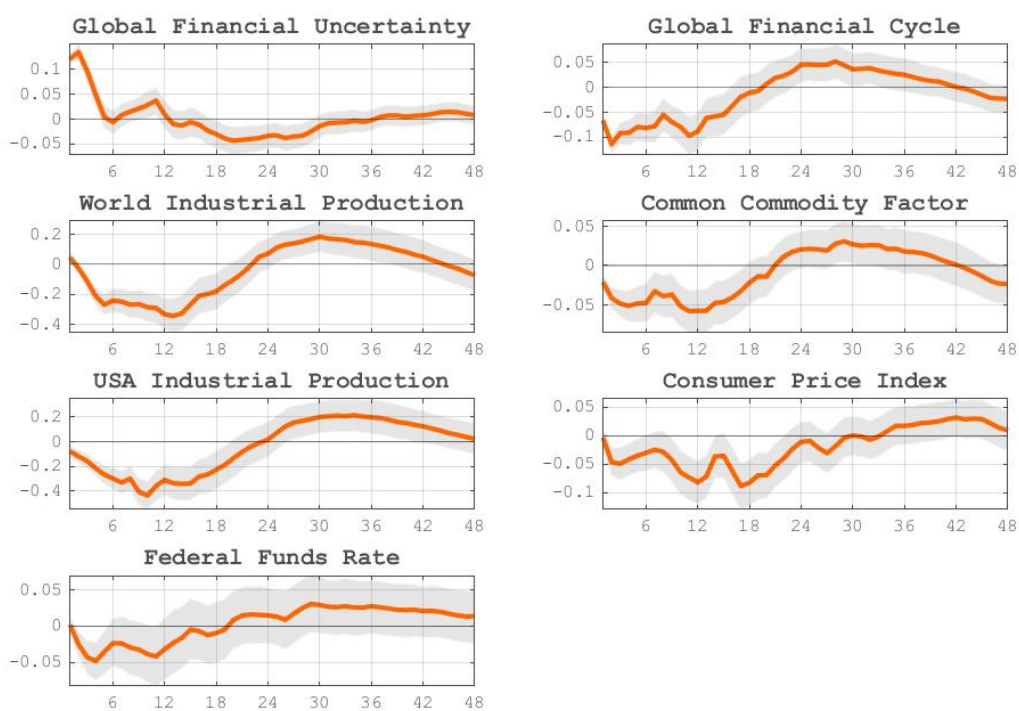
Note: Impulse response function to shock of the Common commodity factor. Estimation sample: 1992m7 - 2019m4. Shaded regions represent the 68% confidence intervals.

Figure 17: Impulse response functions to Federal Fund rate shock, sample: 92m7-19m4



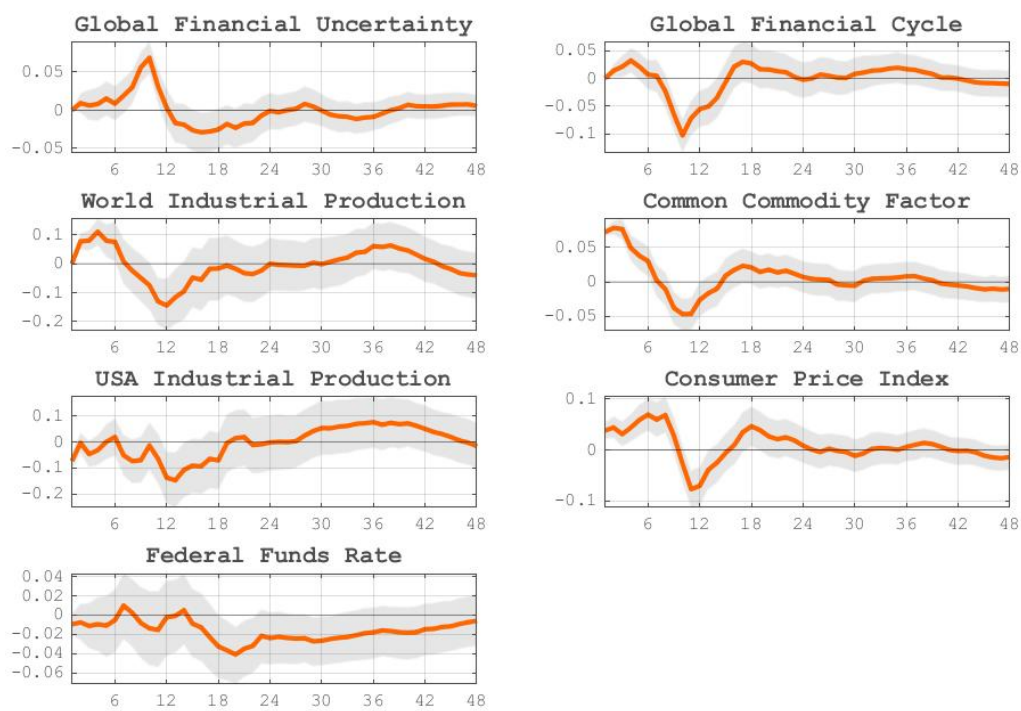
Note: Impulse response function to federal funds rate shock. Estimation sample: 1992m7 - 2019m4. Shaded regions represent the 68% confidence intervals.

Figure 18: Impulse response functions to GFU shocks, sample: 03m8-19m4



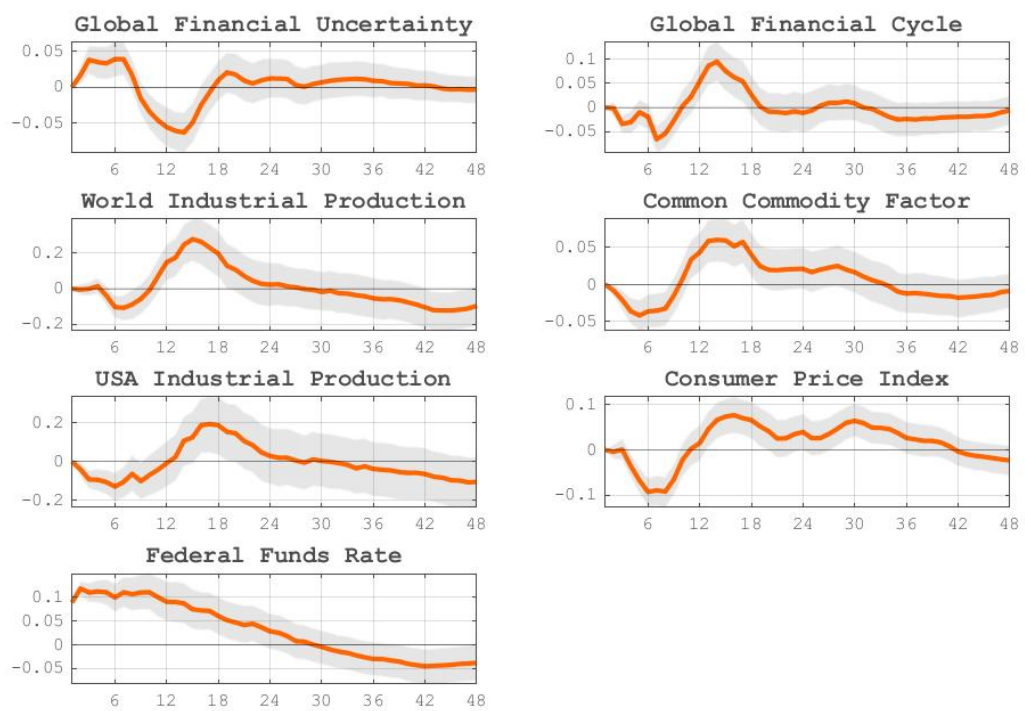
Note: Impulse response function to shock of Global financial Uncertainty factor of Caggiano,Castelnuovo (2021) [20]. Estimation sample: 2003m8 - 2019m4. Shaded regions represent the 68% confidence intervals.

Figure 19: Impulse response functions to CCF shock, sample: 03m8-19m4



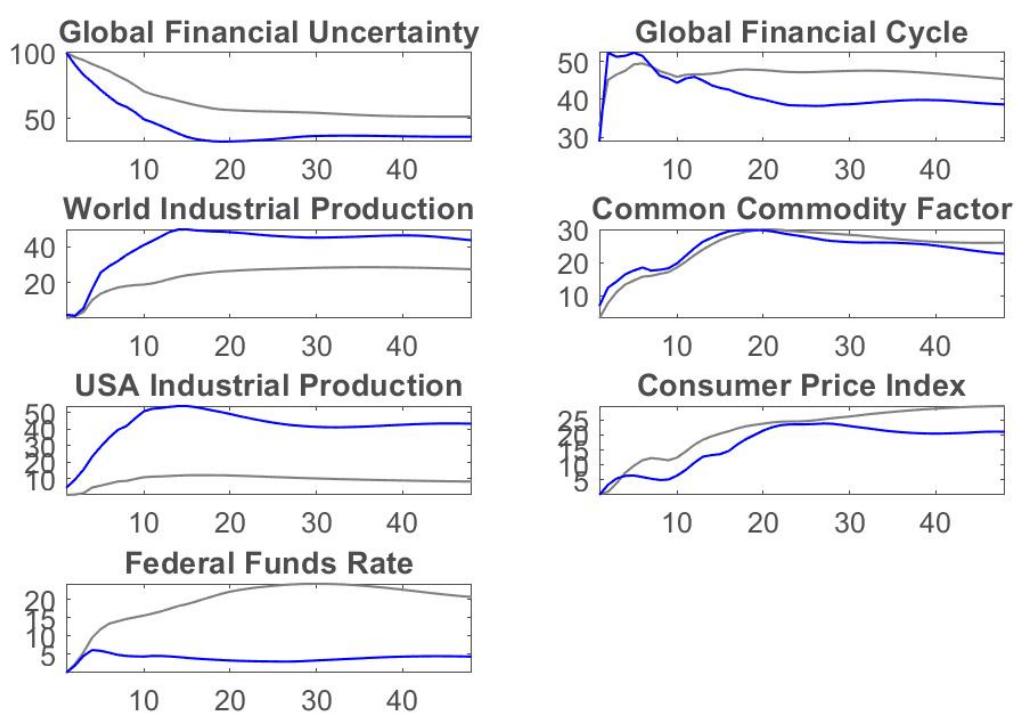
Note: Impulse response function to shock of the Common commodity factor. Estimation sample: 2003m8 - 2019m4. Shaded regions represent the 68% confidence intervals.

Figure 20: Impulse response functions to Federal Fund rate shock, sample: 03m8-19m4



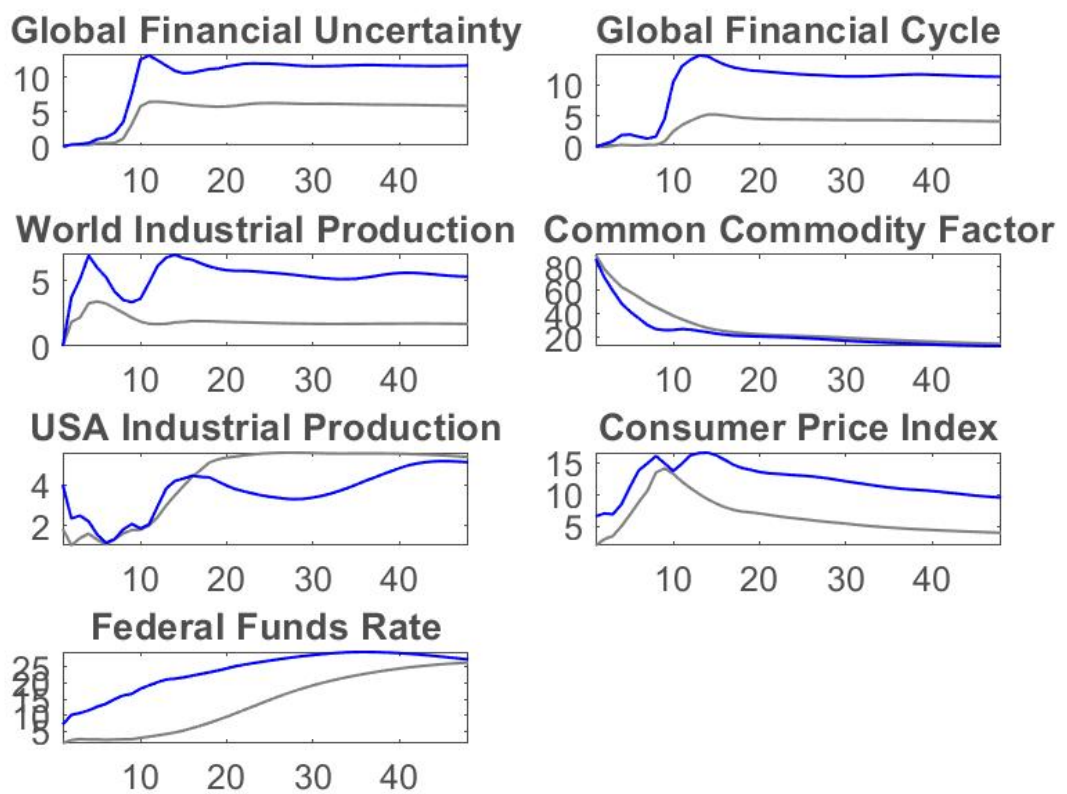
Note: Impulse response function to federal funds rate shock. Estimation sample: 2003m8 - 2019m4. Shaded regions represent the 68% confidence intervals.

Figure 21: Forecast Error Variance Decomposition: GFU



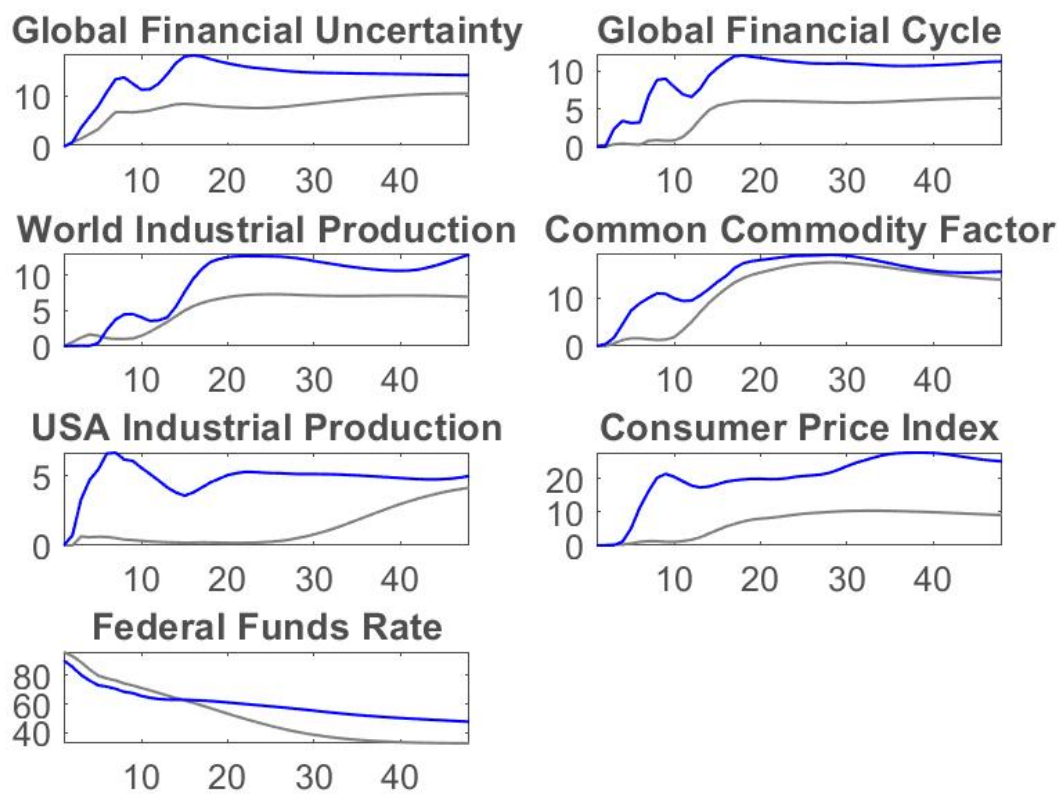
Note: Forecast error variance decomposition of global financial uncertainty shock of Caggiano, Castelnuovo (2021) [20]. Blue line represents the estimation sample 2003m8 - 2019m4, Grey line: 1992m7 - 2019m4.

Figure 22: Forecast Error Variance Decomposition: CCF



Note: Forecast error variance decomposition of the common commodity factor shock. Blue line represents the estimation sample 2003m8 - 2019m4, Grey line: 1992m7 - 2019m4.

Figure 23: Forecast Error Variance Decomposition: federal funds rate



Note: Forecast error variance decomposition of federal funds rate shock. Blue line represents the estimation sample 2003m8 - 2019m4, Grey line: 1992m7 - 2019m4.

MATLAB Codes

We report the most relevant MATLAB codes used in our thesis. The structure of the codes for the Dynamic Factor Model have been provided by Delle Chiaie et al. (2021) [38] at the following link: http://qed.econ.queensu.ca/jae/datasets/delle_chiaie001/. We used the VAR Toolbox 3.0 provided by Ambrogio Cesa- Bianchi to run the VAR analysis, codes are available at: <https://sites.google.com/site/ambropo/MatlabCodes>. Clearly, each code required the appropriate adjustments. First, we show the DFM codes and its principal subroutine to compute the factors. Second, we show the codes for the VAR analysis.

```

%% DFM: main estimate

clear;
clc;
close all;

%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%% Section 1. set path and folders
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%

rootfolder= 'C:\Users\Leonardo\Google Drive\1_UNIPD\16_THESIS\Thesis\DFM';
dataset = strcat(rootfolder, '\data_dfm\'); % data path
    if ~exist(dataset, 'dir')
        mkdir(dataset);
    end
functions = strcat(rootfolder, '\subrutines\dellaCHIAIE\functions'); % functions
    if ~exist(functions, 'dir')
        mkdir(functions);
    end
output = strcat(rootfolder, '\output_rep\'); % results
    if ~exist(output, 'dir')
        mkdir(output);
    end
addpath(dataset); addpath(functions); addpath(output); % output

namesave = strcat('sav_',datestr(today)); % date

%% Section 2: Load data
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%

[DATA,TEXT]= xlsread('CommodityDataRep.xlsx','r_Data'); %for nominal data: 'data', ↵
for real doata r_Data
Time = datenum((TEXT(3:end,1)));
X = DATA;
Mnem = TEXT(1,2:end)';
[DATA,TEXT]= xlsread('CommodityDataRep.xlsx','legend');
Unit = TEXT(2:end,2);
Description = TEXT(2:end,3);
BlockNames = TEXT(1,4:end-1)';
Blocks = DATA(:,1:end-1);
Global = DATA(:,1);
Select = DATA(:,end);
[DATA,TEXT]= xlsread('CommodityDataRep.xlsx','weights');
Weights = DATA;
clear DATA TEXT
disp ('Section 2: Data loaded')

%% Section 3: Create variables and select data for estimation
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%

X = X(:,Select==1);
Global = Global(Select==1);
Description = Description(Select==1);

```

```

Blocks = Blocks(Select==1,:);
Unit = Unit(Select==1);
Mnem = Mnem(Select==1);
Xdfm = X(:,Global==1);
Xind = X(:,Global==0);
MnemDfm = Mnem(Global==1);
BlockDfm = Blocks(Global==1,:);
DescriptionDfm = Description(Global==1);

x = diff(log(Xdfm))*100;
y = diff(log(Xind))*100;

TimeDfm = Time(2:end,:);
DatesDfm = datevec(TimeDfm);

% select estimation sample
BegEstY = 1990; BegEstM = 2;
EndEstY = 2021; EndEstM = 11;

TbegEst = find(DatesDfm(:,1)==BegEstY & DatesDfm(:,3)==BegEstM);
TendEst = find(DatesDfm(:,1)==EndEstY & DatesDfm(:,3)==EndEstM);

xest = x(TbegEst:TendEst,:);
DatesEst = DatesDfm(TbegEst:TendEst,:);
TimeEst = datenum(DatesEst);

[t,m] = size(xest);

xin = xest;

xin(xin==0) = NaN;

% check missing data
SerOK = (sum(isnan(xin))<t/4);

xin= xin(:,SerOK);
Mnemest = MnemDfm(SerOK,1);
Blockest = BlockDfm(SerOK,:);
w = Weights(SerOK,:);
Descriptionest = DescriptionDfm(SerOK,1);
[t,m] = size(xin);

clear X Time TimeDfm load_data
disp('Section 3: Create variables and select data for estimation ends')

%% Section 4: ESTIMATION DFM WITH BLOCKS USING EM ALGORITHM
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%

r = 1; % number of common factors
Par.r = ones(size(Blockest,2),1); Par.r(1) = r; %Number of block factors
Par.p = 1; % Lags in the VAR on the factors
Par.nQ = 0; %n. of quarterly variables, it is necessary for the model to understand
the positions
Par.blocks = [Blockest];

```

```

Par.thresh = 1e-4;
Par.max_iter = 1000;

disp ('Estimation starts')
Res_in = EM_DFM_SS_block_idioQARMA_restrMQ(xin,Par);

clear Select_blocks TbegEst TendEst

disp ('Section 4: Estimation completed')

%% Section 5: FIGURE 1 - The global factor
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%

F_t = Res_in.F(:,1);
imf_index = Res_in.X_sm*w(:,1);
time=(1990+2/12:1/12:2021+11/12)'; % Time line

F_imf=corr(F_t,imf_index)
txt=['\rho: ' num2str(F_imf)]

figure(1)
set(gcf,'PaperPosition',[0 0 18 13])
set(gcf,'papertype','A4letter');
plot(time,imf_index,'LineWidth',0.75)
hold on
plot(time,F_t(:,1),'LineWidth',1)
legend('IMF commodity index','Global Factor','Location','SouthWest')
%legend('Common Commodity Factor','Location','SouthWest')
legend('boxoff')
set(gca,'FontSize',12,'Fontname','Arial');
axis('tight')
text(2015,-16,txt);
ylim([-20 20])

patch([1990.7 1991.5 1991.5 1990.7],[-200 -200 200 200],[0.5 0.5 0.5],'Facealpha',↙
0.5,'Linestyle','none', 'HandleVisibility','off');
patch([2001.3 2002.10 2002.10 2001.3],[-200 -200 200 200],[0.5 0.5 0.5],'Facealpha',↙
0.5,'Linestyle','none', 'HandleVisibility','off');
patch([2007.12 2009.6 2009.6 2007.12],[-200 -200 200 200],[0.5 0.5 0.5],'Facealpha',↙
0.5,'Linestyle','none', 'HandleVisibility','off');
patch([2020.1 2020.3 2020.3 2020.1],[-200 -200 200 200],[0.5 0.5 0.5],'Facealpha',↙
0.5,'Linestyle','none', 'HandleVisibility','off');

filename = fullfile(output, 'CCF');
savefig(filename);
print(filename,'-djpeg');
clear time

disp ('Section 5: Figure 1 saved')

%% Section 6: Load additional data
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
[DATA,TEXT]= xlsread('Economic_Indicators.xlsx','data');
Time = datenum((TEXT(2:end,1)));

```



```

X = DATA(:,1:end);
Mnem = TEXT(1,2:end)';
clear DATA TEXT

% select sample
Dates = datevec(Time);
%
BegY = 1990; BegM = 2;
EndY = 2021; EndM = 11;
%
TbegEst = find(Dates(:,1)==BegEstY & Dates(:,3)==BegEstM);
TendEst = find(Dates(:,1)==EndEstY & Dates(:,3)==EndEstM);

Y = X(TbegEst:TendEst,:);

clear Text X BegEstY EndEstY TbegEst TendEst

% transform the global factor and select sample
h=12;

y = (filter(ones(1, h) / h, 1, F_t(:,1)))*12;

BegY = 1990; BegM = 2;
EndY = 2021; EndM = 11;
%
Tbeg = find(DatesEst(:,1)==BegY & DatesEst(:,3)==BegM);
Tend = find(DatesEst(:,1)==EndY & DatesEst(:,3)==EndM);

yplot = y(Tbeg:Tend,1);

clear Da* T* E*

disp('Section 6: Other data loaded')
%
%% Section 7: FIGURE 2 - the global factor and other measures of global economic activity
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
GF_t = yplot;% global factor

K_t = Y(:,1); % Kilian index (2009,2019)
IP_t = Y(:,2);% OECD + 6 IP (as in Baumeister and Hamilton, 2019)

corr_K=corr(GF_t,K_t)
txt1=['\rho: ' num2str(corr_K)]
corr_ip=corr(GF_t,IP_t)
txt2=['\rho: ' num2str(corr_ip)]

time=(1990+2/12:1/12:2021+11/12)';

figure(2)
set(gcf,'PaperPosition',[0 0 15 15])
set(gcf,'papertype','A4letter');
subplot(2,1,1)
yyaxis left

```

```

plot(time,K_t,'LineWidth',1)
yyaxis right
plot(time,GF_t,'LineWidth',1)
ylim([-50 50])
set(gca,'FontSize',12,'Fontname','Arial','xlim',[1990.2 2021.11]);
text(2015,40,txt1);
legend('Kilian index', 'Common Commodity Factor','Location','southwest');
legend('boxoff');

% NBER recession bars
patch([1990.7 1991.5 1991.5 1990.7],[-200 -200 200 200],[0.5 0.5 0.5],'Facealpha',↙
0.5,'Linestyle','none', 'HandleVisibility','off');
patch([2001.3 2002.10 2002.10 2001.3],[-200 -200 200 200],[0.5 0.5 0.5],'Facealpha',↙
0.5,'Linestyle','none', 'HandleVisibility','off');
patch([2007.12 2009.6 2009.6 2007.12],[-200 -200 200 200],[0.5 0.5 0.5],'Facealpha',↙
0.5,'Linestyle','none', 'HandleVisibility','off');
patch([2020.1 2020.3 2020.3 2020.1],[-200 -200 200 200],[0.5 0.5 0.5],'Facealpha',↙
0.5,'Linestyle','none', 'HandleVisibility','off');

subplot(2,1,2)
yyaxis left
plot(time,IP_t,'LineWidth',1)
yyaxis right
plot(time,GF_t,'LineWidth',1)
ylim([-50 50])
set(gca,'FontSize',12,'Fontname','Arial','xlim',[1990.2 2021.11]);
text(2015,40,txt2);
legend('World Industrial Production', 'Common Commodity↙
Factor','Location','southwest');
legend('boxoff')

% NBER recession bars
patch([1990.7 1991.5 1991.5 1990.7],[-200 -200 200 200],[0.5 0.5 0.5],'Facealpha',↙
0.5,'Linestyle','none', 'HandleVisibility','off');
patch([2001.3 2002.10 2002.10 2001.3],[-200 -200 200 200],[0.5 0.5 0.5],'Facealpha',↙
0.5,'Linestyle','none', 'HandleVisibility','off');
patch([2007.12 2009.6 2009.6 2007.12],[-200 -200 200 200],[0.5 0.5 0.5],'Facealpha',↙
0.5,'Linestyle','none', 'HandleVisibility','off');
patch([2020.1 2020.3 2020.3 2020.1],[-200 -200 200 200],[0.5 0.5 0.5],'Facealpha',↙
0.5,'Linestyle','none', 'HandleVisibility','off');
filename = fullfile(output, 'WIP AND KILLIAN');
savefig(filename);
print(filename,'-djpeg');

clear IP_t K_t imf_index
disp ('Section 7: Figure 2 saved')

%% Section 7.B: FIGURE 2.A - the global factor, GFU, GFC
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%

gfu_t = Y(:,3); % GFU
gfc_t = Y(:,4); % GFC

time=(1990+2/12:1/12:2021+11/12)';

```

```
corr_gfu=corrcoef([GF_t,gfu_t], 'Rows', 'pairwise');
corr_gfc=corrcoef([GF_t,gfc_t], 'Rows', 'pairwise');

txt1= ['\rho: ' num2str(corr_gfu(1,2))];
txt2= ['\rho: ' num2str(corr_gfc(1,2))];

figure
set(gcf, 'PaperPosition', [0 0 15 15])
set(gcf, 'papertype', 'A4letter');
subplot(2,1,1)
yyaxis left
plot(time,gfu_t, 'LineWidth',1)
yyaxis right
plot(time,GF_t, 'LineWidth',1)
ylim([-50 50])
set(gca, 'FontSize',12, 'Fontname', 'Arial', 'xlim', [1990.2 2021.11]);
text(2015,40,txt1)
legend('Global Financial Uncertainty', 'Common Commodity
Factor', 'Location', 'northwest');
legend('boxoff');

% NBER recession bars
patch([1990.7 1991.5 1991.5 1990.7], [-200 -200 200 200], [0.5 0.5 0.5], 'Facealpha',
0.5, 'Linestyle', 'none', 'HandleVisibility', 'off');
patch([2001.3 2002.10 2002.10 2001.3], [-200 -200 200 200], [0.5 0.5 0.5], 'Facealpha',
0.5, 'Linestyle', 'none', 'HandleVisibility', 'off');
patch([2007.12 2009.6 2009.6 2007.12], [-200 -200 200 200], [0.5 0.5 0.5], 'Facealpha',
0.5, 'Linestyle', 'none', 'HandleVisibility', 'off');
patch([2020.1 2020.3 2020.3 2020.1], [-200 -200 200 200], [0.5 0.5 0.5], 'Facealpha',
0.5, 'Linestyle', 'none', 'HandleVisibility', 'off');

subplot(2,1,2)
yyaxis left
plot(time,gfc_t, 'LineWidth',1)
yyaxis right
plot(time,GF_t, 'LineWidth',1)
ylim([-50 50])
set(gca, 'FontSize',12, 'Fontname', 'Arial', 'xlim', [1990.2 2021.11]);
text(2015,-40,txt2)
legend('Global Financial Factor', 'Common Commodity Factor', 'Location', 'southwest');
legend('boxoff')

% NBER recession bars
patch([1990.7 1991.5 1991.5 1990.7], [-200 -200 200 200], [0.5 0.5 0.5], 'Facealpha',
0.5, 'Linestyle', 'none', 'HandleVisibility', 'off');
patch([2001.3 2002.10 2002.10 2001.3], [-200 -200 200 200], [0.5 0.5 0.5], 'Facealpha',
0.5, 'Linestyle', 'none', 'HandleVisibility', 'off');
patch([2007.12 2009.6 2009.6 2007.12], [-200 -200 200 200], [0.5 0.5 0.5], 'Facealpha',
0.5, 'Linestyle', 'none', 'HandleVisibility', 'off');
patch([2020.1 2020.3 2020.3 2020.1], [-200 -200 200 200], [0.5 0.5 0.5], 'Facealpha',
0.5, 'Linestyle', 'none', 'HandleVisibility', 'off');
filename = fullfile(output, 'CCF GFU GFC');
savefig(filename);
```

```

print(filename, '-djpeg');

clear IP_t K_t imf_index
disp ('Section 7.A: Figure 2.B saved')

%% Section 8: FIGURE 3 - Factor loadings
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
C = Res_in.C(:,1).*Res_in.Wx';

set(gcf, 'papertype', 'A4letter');
subplot(1,2,1)
barh(C(1:floor(size(C,1)/2),1),0.8)
colormap(cool)
xlim([0 2.1]);
set(gca, 'YTick', 1:1:size(xin(1:(floor(size(C,1)/2)),2))
set(gca, 'YTickLabel', Mnemest(1:(floor(size(C,1)/2)),1), 'FontSize', 8)
%set(gca, 'XTickLabelRotation', 90)

subplot(1,2,2)
barh(C((floor(size(C,1)/2)+1):end,1),0.8)
colormap(cool)
xlim([0 2.1]);
set(gca, 'YTick', 1:1:size(xin((floor(size(C,1)/2)+1):size(C,1)),2))
set(gca, 'YTickLabel', Mnemest((floor(size(C,1)/2)+1):size(C,1),1), 'FontSize', 8)
%set(gca, 'YTickLabelRotation', 90)

filename = fullfile(output, 'Loadings');
savefig(filename);
print(filename, '-djpeg');

disp ('Section 8: Figure 3 saved')

%% Section 9: Figure 4 Common components

% Copper (9)
% Brent crude oil (21)

a = find(strcmp(Mnemest, 'Copper'));
b = find(strcmp(Mnemest, 'Brent Crude Oil'));
%
Gamma_a = (Res_in.Wx(1,a)).*(Res_in.C(a,1)*F_t(:,1))+Res_in.Mx(1,a);
Gamma_b = (Res_in.Wx(1,b)).*(Res_in.C(b,1)*F_t(:,1))+Res_in.Mx(1,b);

h = 12;

y_c = filter(ones(h,1)/h,1, Gamma_a);
y_o = filter(ones(h,1)/h,1, Gamma_b);
cop_f = filter(ones(h,1)/h,1, Res_in.X_sm(:,a));
oil_f = filter(ones(h,1)/h,1, Res_in.X_sm(:,b));

figure(4)
set(gcf, 'PaperPosition', [0 0 15 15])
set(gcf, 'papertype', 'A4letter');
subplot(2,1,1)

```

```

time=(1990+2/12:1/12:2021+11/12)';

plot(time, oil_f, ':', 'Color', [0 0 0.7], 'LineWidth', 1)
hold on
plot(time, cop_f, ':', 'Color', [0, 0.6, 0.3], 'LineWidth', 1)
plot(time, y_o, 'Color', [0 0 0.7], 'LineWidth', 1.5)
plot(time, y_c, 'Color', [0, 0.6, 0.3], 'LineWidth', 1.5)
legend('Copper', 'Brent Oil', 'Common component of copper', 'Common component of oil', 'Location', 'SouthEast')
legend('Copper', 'Brent Oil', 'Location', 'SouthEast')
legend BOXOFF
set(gca, 'FontSize', 12, 'Fontname', 'Arial', 'xlim', [1992.1 2021.11]);
hold off

subplot(2,1,2)
plot(time, (oil_f-cop_f), ':', time, (y_o-y_c), 'LineWidth', 1)
legend('Relative prices', 'Relative common components', 'Location', 'SouthEast')
legend BOXOFF
set(gca, 'FontSize', 12, 'Fontname', 'Arial', 'xlim', [1992.1 2021.11]);

clear G*
filename = fullfile(output, 'Common Components');
savefig(filename);
print(filename, '-djpeg');

disp ('Section 9: Figure 4 saved')
disp ('Main_est ended')

%% Added Section 1 Nominal vs Real
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%

%loading data
[DATA,TEXT]= xlsread('CCF.xlsx', 'data');
Time = datenum((TEXT(2:end,1)));
X = DATA(:,1:end);
Mnem = TEXT(1,2:end)';
clear DATA TEXT

% select sample
Dates = datevec(Time);
%
BegY = 1992; BegM = 1;
EndY = 2021; EndM = 11;
%
TbegEst = find(Dates(:,1)==BegY & Dates(:,3)==BegM);
TendEst = find(Dates(:,1)==EndY & Dates(:,3)==EndM);

Y = X(TbegEst:TendEst,:);

% plotting data

time=(1992+1/12:1/12:2021+11/12)';

```

```

%not transformed
N_CCF = Y(:,1);
R_CCF = Y(:,2);

NR_corr = corr(N_CCF,R_CCF);

%transformed
N_CCF_yoy = Y(:,5);
R_CCF_yoy = Y(:,6);

NR_corr_yoy = corr(N_CCF_yoy,R_CCF_yoy);

%text on plots
txt1= ['\rho: ' num2str(NR_corr)];
txt2= ['\rho: ' num2str(NR_corr_yoy)];

%plots
figure
set(gcf, 'PaperPosition',[0 0 15 15])
set(gcf, 'papertype', 'A4letter');
subplot(2,1,1)
plot(time,N_CCF, 'LineWidth', .75);
hold on
plot(time,R_CCF, 'LineWidth', .7)
set(gca, 'FontSize',12, 'Fontname', 'Arial', 'xlim', [1992.1 2021.11]);
text(1995,-10,txt1)
legend('Nominal', 'Real', 'Location', 'southeast');
legend('boxoff');

subplot(2,1,2)
yyaxis left
plot(time,N_CCF_yoy, 'LineWidth',1);
yyaxis right
plot(time,R_CCF_yoy, 'LineWidth',1)

set(gca, 'FontSize',12, 'Fontname', 'Arial', 'xlim', [1992.1 2021.11]);
text(1995,-35,txt2);
legend('Nominal', 'Real', 'Location', 'southeast');
legend('boxoff')

filename = fullfile(output, 'RealVsNominal');
savefig(filename);
print(filename, '-djpeg');

disp ('Additional Section 1 finish')

%% Added Section 2 full sample vs shorter sample
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%

%loading data
[DATA,TEXT]= xlsread('CCF.xlsx', 'data');
Time = datenum((TEXT(2:end,1)));
X = DATA(:,1:end);
Mnem = TEXT(1,2:end)';

```

```
clear DATA TEXT

% select sample
Dates = datevec(Time);
%
BegY = 1992; BegM = 1;
EndY = 2019; EndM = 11;
%
TbegEst = find(Dates(:,1)==BegY & Dates(:,3)==BegM);
TendEst = find(Dates(:,1)==EndY & Dates(:,3)==EndM);

Y = X(TbegEst:TendEst,:);

% plotting data

time=(1992+1/12:1/12:2019+11/12)';

%not transformed
N_CCF = Y(:,1);
N_CCF19 = Y(:,3);

NR_corr = corr(N_CCF,N_CCF19);

%transformed
N_CCF_yoy = Y(:,5);
N_CCF_yoy19 = Y(:,4);

NR_corr_yoy = corr(N_CCF_yoy,N_CCF_yoy19);

%text on plots
txt1= ['\rho: ' num2str(NR_corr)];
txt2= ['\rho: ' num2str(NR_corr_yoy)];

%plots
figure
set(gcf,'PaperPosition',[0 0 15 15])
set(gcf,'papertype','A4letter');
subplot(2,1,1)
yyaxis left
plot(time,N_CCF,'LineWidth',1);
yyaxis right
plot(time,N_CCF19,'LineWidth',1)

set(gca,'FontSize',12,'Fontname','Arial','xlim',[1992.1 2019.11]);
text(2013,-15,txt1)
legend('Sample: 90m2-21m11', 'Sample: 92m1-19m11','Location','southwest');
legend('boxoff');

subplot(2,1,2)
yyaxis left
plot(time,N_CCF_yoy,'LineWidth',1);
yyaxis right
plot(time,N_CCF_yoy19,'LineWidth',1)
set(gca,'FontSize',12,'Fontname','Arial','xlim',[1992.1 2019.11]);
```

```
text(2013,-35,txt2);
legend('Sample: 90m2-21m11', 'Sample: 92m1-19m11','Location','southwest');
legend('boxoff')

filename = fullfile(output, 'Fullsamplevsshorter');
savefig(filename);
print(filename, '-djpeg');

disp ('Additional Section 2 finish')

%% Added Section 3 My CCF vs Author
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%

%loading data
[DATA,TEXT]= xlsread('CCF.xlsx','Author CCF');
Time = datenum((TEXT(2:end,1)));
X = DATA(:,1:end);
Mnem = TEXT(1,2:end)';
clear DATA TEXT

% select sample
Dates = datevec(Time);
%
BegY = 1990; BegM = 2;
EndY = 2020; EndM = 3;
%
TbegEst = find(Dates(:,1)==BegY & Dates(:,3)==BegM);
TendEst = find(Dates(:,1)==EndY & Dates(:,3)==EndM);

Y = X(TbegEst:TendEst,:);

% plotting data

time=(1990+2/12:1/12:2020+3/12)';

%not transformed
N_CCF = Y(:,1);
A_CCF = Y(:,2); %2017 dataset

NA_corr = corr(N_CCF,A_CCF);

%text on plots
txt1= ['\rho: ' num2str(NA_corr)];

%plots
figure
set(gcf,'PaperPosition',[0 0 18 13])
set(gcf,'papertype','A4letter');
plot(time,N_CCF,'LineWidth',1);
hold on
plot(time,A_CCF,'LineWidth',1);

set(gca,'FontSize',12,'Fontname','Arial','xlim',[1990.2 2020.3]);
text(2015,-15,txt1)
```



```

legend('Common Commodity Factor', 'Delle Chiaie et All. (2017)', 'Location', 'southwest');
legend('boxoff');

filename = fullfile(output, 'Author Factor');
savefig(filename);
print(filename, '-djpeg');

disp ('Additional Section 3 finish')

%% Added Section 4 CUMSUM real CCF
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%loading data
[DATA,TEXT]= xlsread('CCF.xlsx','data');
Time = datenum((TEXT(2:end,1)));
X = DATA(:,1:end);
Mnem = TEXT(1,2:end)';
clear DATA TEXT

% select sample
Dates = datevec(Time);
%
BegY = 1990; BegM = 2;
EndY = 2021; EndM = 11;
%
TbegEst = find(Dates(:,1)==BegY & Dates(:,3)==BegM);
TendEst = find(Dates(:,1)==EndY & Dates(:,3)==EndM);

Y = X(TbegEst:TendEst,:);

%not transformed
Cumsum_R_CCF = normalize(Y(:,7));
CPB_World_Trade = normalize(Y(:,8));

A = [Cumsum_R_CCF CPB_World_Trade];

corr = corrcoef(A, 'Rows', 'pairwise');

%text on plots
txt1= ['\rho: ' num2str(corr(1,2))];

% plotting data
time=(1990+2/12:1/12:2021+11/12)';

%plots
figure
set(gcf, 'PaperPosition', [0 0 20 15])
set(gcf, 'papertype', 'A4letter');
plot(time, Cumsum_R_CCF, 'LineWidth', 1);
hold on
plot(time, CPB_World_Trade, 'LineWidth', 1);

set(gca, 'FontSize', 12, 'Fontname', 'Arial', 'xlim', [1990.2 2021.11]);
text(2015, -2, txt1)

```

```
legend('Cumulative CCF', 'CPB World Trade Measure', 'Location', 'northwest');  
legend('boxoff');
```

```
filename = fullfile(output, 'Cumulative Factor');  
savefig(filename);  
print(filename, '-djpeg');
```

```
disp ('Additional Section 4 finish')
```

```
%% Added Section 5 real CCF and import terms of trade  
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
```

```
%loading data  
[DATA,TEXT]= xlsread('Terms of trade.xlsx','data');  
Time = datenum((TEXT(2:end,1)));  
X = DATA(:,1:end);  
Mnem = TEXT(1,2:end)';  
clear DATA TEXT
```

```
% select sample  
Dates = datevec(Time);  
%  
BegY = 1992; BegM = 1;  
EndY = 2021; EndM = 11;  
%  
TbegEst = find(Dates(:,1)==BegY & Dates(:,3)==BegM);  
TendEst = find(Dates(:,1)==EndY & Dates(:,3)==EndM);
```

```
Y = X(TbegEst:TendEst,:);
```

```
%not transformed  
Cumsum_R_CCF = normalize(Y(:,1));  
Brazil = normalize(Y(:,2));  
Russia = normalize(Y(:,3));  
India = normalize(Y(:,4));  
China = normalize(Y(:,5));  
Germany = normalize(Y(:,6));  
France = normalize(Y(:,7));  
UK = normalize(Y(:,8));  
US = normalize(Y(:,9));  
Italy = normalize(Y(:,10));
```

```
A = [Cumsum_R_CCF, Brazil, Russia, China, UK, US];
```

```
corr = corrcoef(A);
```

```
%text on plots  
%txt1= ['\rho: ' num2str(corr(1,2))];
```

```
% plotting data  
time=(1992+1/12:1/12:2021+11/12)';
```

```
%plots  
figure  
set(gcf, 'PaperPosition', [0 0 20 15])
```

```

set(gcf,'papertype','A4letter');
plot(time,Cumsum_R_CCF,'LineWidth',1);
hold on
plot(time,Russia,'LineWidth',1);
hold on
plot(time,China,'LineWidth',1);
hold on
plot(time,UK,'LineWidth',1);
hold on
plot(time,US,'LineWidth',1);

set(gca,'FontSize',12,'Fontname','Arial','xlim',[1992.1 2021.11]);
%text(2015,-2,txt1)
legend('CCF','Russia','China','UK','US','Location','northwest');
legend('boxoff');

%
% patch([1990.7 1991.5 1991.5 1990.7],[-200 -200 200 200],[0.5 0.5 0.5],'Facealpha',
0.5,'Linestyle','none','HandleVisibility','off');
% patch([2001.3 2002.10 2002.10 2001.3],[-200 -200 200 200],[0.5 0.5
0.5],'Facealpha',0.5,'Linestyle','none','HandleVisibility','off');
% patch([2007.12 2009.6 2009.6 2007.12],[-200 -200 200 200],[0.5 0.5
0.5],'Facealpha',0.5,'Linestyle','none','HandleVisibility','off');
% patch([2020.1 2020.3 2020.3 2020.1],[-200 -200 200 200],[0.5 0.5 0.5],'Facealpha',
0.5,'Linestyle','none','HandleVisibility','off');

filename = fullfile(output, 'Terms of Trade_import');
savefig(filename);
print(filename, '-djpeg');

disp ('Additional Section 5 finish')

%% Added Section 6 real CCF and export terms of trade
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%loading data
[DATA,TEXT]= xlsread('Terms of trade.xlsx','export');
Time = datenum((TEXT(2:end,1)));
X = DATA(:,1:end);
Mnem = TEXT(1,2:end)';
clear DATA TEXT

% select sample
Dates = datevec(Time);
%
BegY = 1992; BegM = 1;
EndY = 2021; EndM = 11;
%
TbegEst = find(Dates(:,1)==BegY & Dates(:,3)==BegM);
TendEst = find(Dates(:,1)==EndY & Dates(:,3)==EndM);

Y = X(TbegEst:TendEst,:);

%not transformed
Cumsum_R_CCF = normalize(Y(:,1));

```



```
%loading data
[DATA,TEXT]= xlsread('Terms of trade.xlsx','netflows');
Time = datenum((TEXT(2:end,1)));
X = DATA(:,1:end);
Mnem = TEXT(1,2:end)';
clear DATA TEXT

% select sample
Dates = datevec(Time);
%
BegY = 1992; BegM = 1;
EndY = 2021; EndM = 11;
%
TbegEst = find(Dates(:,1)==BegY & Dates(:,3)==BegM);
TendEst = find(Dates(:,1)==EndY & Dates(:,3)==EndM);

Y = X(TbegEst:TendEst,:);

%not transformed
Cumsum_R_CCF = normalize(Y(:,1));

Russia = normalize(Y(:,2));
China = normalize(Y(:,3));
UK = normalize(Y(:,4));
US = normalize(Y(:,5));

A = [Cumsum_R_CCF, Russia, China, UK, US];

corr = corrcoef(A);

%text on plots
%txt1= ['\rho: ' num2str(corr(1,2))];

% plotting data
time=(1992+1/12:1/12:2021+11/12)';

%plots
figure
set(gcf,'PaperPosition',[0 0 20 15])
set(gcf,'papertype','A4letter');
plot(time,Cumsum_R_CCF,'LineWidth',1);
hold on
plot(time,Russia,'LineWidth',1);
hold on
plot(time,China,'LineWidth',1);
hold on
plot(time,UK,'LineWidth',1);
hold on
plot(time,US,'LineWidth',1);

set(gca,'FontSize',12,'Fontname','Arial','xlim',[1992.1 2021.11]);
%text(2015,-2,txt1)
legend('CCF', 'Russia', 'China', 'UK', 'US', 'Location', 'northwest');
```

```

legend('boxoff');

filename = fullfile(output, 'Terms of Trade_netflow');
savefig(filename);
print(filename, '-djpeg');

disp ('Additional Section 7 finish')

%% Section 8: FIGURE 2.A - GFU, GFC
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
[DATA,TEXT]= xlsread('Economic_Indicators.xlsx','data');
Time = datenum((TEXT(2:end,1)));
X = DATA(:,1:end);
Mnem = TEXT(1,2:end)';
clear DATA TEXT

% select sample
Dates = datevec(Time);
%
BegY = 1992; BegM = 7;
EndY = 2020; EndM = 5;
%
TbegEst = find(Dates(:,1)==BegY & Dates(:,3)==BegM);
TendEst = find(Dates(:,1)==EndY & Dates(:,3)==EndM);

gfu_t = X(TbegEst:TendEst,3);

%
BegY = 1980; BegM = 1;
EndY = 2019; EndM = 4;
%
TbegEst = find(Dates(:,1)==BegY & Dates(:,3)==BegM);
TendEst = find(Dates(:,1)==EndY & Dates(:,3)==EndM);

gfc_t = X(TbegEst:TendEst,4);

clear Text X BegEstY EndEstY TbegEst TendEst

figure
set(gcf,'PaperPosition',[0 0 20 15])
set(gcf,'papertype','A4letter');

time=(1980+1/12:1/12:2019+4/12)';
plot(time,gfc_t,'LineWidth',1)
ylim([-3.5 3.5])
set(gca,'FontSize',12,'Fontname','Arial','xlim',[1980.1 2019.4]);
legend('Global Financial Factor','Location','northwest');
legend('boxoff');

% NBER recession bars
patch([1990.7 1991.5 1991.5 1990.7],[-200 -200 200 200],[0.5 0.5 0.5],'Facealpha',\
0.5,'Linestyle','none','HandleVisibility','off');

```

```

patch([2001.3 2002.10 2002.10 2001.3],[-200 -200 200 200],[0.5 0.5 0.5],'Facealpha',↵
0.5,'Linestyle','none', 'HandleVisibility','off');
patch([2007.12 2009.6 2009.6 2007.12],[-200 -200 200 200],[0.5 0.5 0.5],'Facealpha',↵
0.5,'Linestyle','none', 'HandleVisibility','off');
patch([2020.1 2020.3 2020.3 2020.1],[-200 -200 200 200],[0.5 0.5 0.5],'Facealpha',↵
0.5,'Linestyle','none', 'HandleVisibility','off');

filename = fullfile(output, 'GFC');
savefig(filename);
print(filename, '-djpeg');

figurefigure
set(gcf, 'PaperPosition',[0 0 20 15])
set(gcf, 'papertype', 'A4letter');

time=(1992+7/12:1/12:2020+5/12)';
plot(time,gfu_t, 'LineWidth',1)
ylim([-1 3.6])
set(gca, 'FontSize',12, 'Fontname', 'Arial', 'xlim', [1992.7 2020.5]);
legend('Global Financial Uncertainty', 'Location', 'northwest');
legend('boxoff')

% NBER recession bars
patch([1990.7 1991.5 1991.5 1990.7],[-200 -200 200 200],[0.5 0.5 0.5],'Facealpha',↵
0.5,'Linestyle','none', 'HandleVisibility','off');
patch([2001.3 2002.10 2002.10 2001.3],[-200 -200 200 200],[0.5 0.5 0.5],'Facealpha',↵
0.5,'Linestyle','none', 'HandleVisibility','off');
patch([2007.12 2009.6 2009.6 2007.12],[-200 -200 200 200],[0.5 0.5 0.5],'Facealpha',↵
0.5,'Linestyle','none', 'HandleVisibility','off');
patch([2020.1 2020.3 2020.3 2020.1],[-200 -200 200 200],[0.5 0.5 0.5],'Facealpha',↵
0.5,'Linestyle','none', 'HandleVisibility','off');

filename = fullfile(output, 'GFU');
savefig(filename);
print(filename, '-djpeg');

clear IP_t K_t imf_index
disp('Section 7.A: Figure 2.B saved')
%% Section 8: FIGURE 2.A - SR
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
[DATA,TEXT]= xlsread('C:\Users\Leonardo\Google↵
Drive\1_UNIPD\16_THESIS\Thesis\Final_results\Data\data.xlsx', 'SR');
Time = datenum((TEXT(2:end,1)));
X = DATA(:,1:end);
Mnem = TEXT(1,2:end)';
clear DATA TEXT

% select sample
Dates = datevec(Time);
%
BegY = 1990; BegM = 1;
EndY = 2022; EndM = 2;
%
```

```
TbegEst = find(Dates(:,1)==BegY & Dates(:,3)==BegM);
TendEst = find(Dates(:,1)==EndY & Dates(:,3)==EndM);

effr_t = X(TbegEst:TendEst,1)
sr_t = X(TbegEst:TendEst,2);

clear Text X BegEstY EndEstY TbegEst TendEst

time=(1990+1/12:1/12:2022+2/12)';

figure
set(gcf,'PaperPosition',[0 0 20 15])
set(gcf,'papertype','A4letter');
plot(time,effr_t,'LineWidth',1);
hold on
plot(time,sr_t,'LineWidth',1);
hold on
line(xlim, [0,0], 'Color', 'k', 'LineWidth', 0.5, 'LineStyle', '--');

set(gca,'FontSize',12,'Fontname','Arial','xlim',[1990.1 2022.2]);
legend('EFFR','Shadow Rate','Location','southwest');
legend('boxoff');

patch([2009.1 2016.1 2016.1 2009.1],[-4 -4 10 10],[0.5 0.5 0.5],'Facealpha',0.3,'LineStyle','none','HandleVisibility','off');

filename = fullfile(output, 'SR');
savefig(filename);
print(filename, '-djpeg');

clear IP_t K_t imf_index
disp('Section 7.A: Figure 2.B saved')
```



```
%% DFM: hist decomp

clear;
clc;
close all;

%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%% Section 1. set path and folders
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%

rootfolder= 'C:\Users\Leonardo\Google Drive\1_UNIPD\16_THESIS\Thesis\DFM';
dataset = strcat(rootfolder, '\data_dfm\'); % data path
    if ~exist(dataset, 'dir')
        mkdir(dataset);
    end
functions = strcat(rootfolder, '\subrutines\dellaCHIAIE\functions'); % functions
    if ~exist(functions, 'dir')
        mkdir(functions);
    end
output = strcat(rootfolder, '\output_rep\'); % results
    if ~exist(output, 'dir')
        mkdir(output);
    end
addpath(dataset); addpath(functions); addpath(output); % output

namesave = strcat('sav_',datestr(today)); % date

%% Section 2: Load data
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%

[DATA,TEXT]= xlsread('CommodityDataRep.xlsx','r_Data'); %for nominal data: 'data'
Time = datenum((TEXT(3:end,1)));
X = DATA;
Mnem = TEXT(1,2:end)';
[DATA,TEXT]= xlsread('CommodityDataRep.xlsx','legend');
Unit = TEXT(2:end,2);
Description = TEXT(2:end,3);
BlockNames = TEXT(1,4:end-1)';
Blocks = DATA(:,1:end-1);
Global = DATA(:,1);
Select = DATA(:,end);
[DATA,TEXT]= xlsread('CommodityDataRep.xlsx','weights');
Weights = DATA;
clear DATA TEXT
disp ('Section 2: Data loaded')

%% Section 3: Create variables and select data for estimation
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%

X = X(:,Select==1);
Global = Global(Select==1);
Description = Description(Select==1);
Blocks = Blocks(Select==1,:);
```

```

Unit = Unit(Select==1);
Mnem = Mnem(Select==1);
Xdfm = X(:,Global==1);
Xind = X(:,Global==0);
MnemDfm = Mnem(Global==1);
BlockDfm = Blocks(Global==1,:);
DescriptionDfm = Description(Global==1);

x = diff(log(Xdfm))*100;
%y = diff(log(Xind))*100;

TimeDfm = Time(2:end,:);
DatesDfm = datevec(TimeDfm);

% select estimation sample
BegEstY = 1990; BegEstM = 2;
EndEstY = 2021; EndEstM = 11;

TbegEst = find(DatesDfm(:,1)==BegEstY & DatesDfm(:,3)==BegEstM);
TendEst = find(DatesDfm(:,1)==EndEstY & DatesDfm(:,3)==EndEstM);

xest = x(TbegEst:TendEst,:);
DatesEst = DatesDfm(TbegEst:TendEst,:);
TimeEst = datenum(DatesEst);

[t,m] = size(xest);

xin = xest;

xin(xin==0) = NaN;

% check missing data
SerOK = (sum(isnan(xin))<t/4);

xin= xin(:,SerOK);
Mnemest = MnemDfm(SerOK,1);
Blockest = BlockDfm(SerOK,:);
w = Weights(SerOK,:);
Descriptionest = DescriptionDfm(SerOK,1);
[t,m] = size(xin);

clear X Time TimeDfm load_data
disp ('Section 3: Create variables and select data for estimation ends')

%% Section 4: ESTIMATION DFM WITH BLOCKS USING EM ALGORITHM
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%

r = 1; % number of common factors
Par.r = ones(size(Blockest,2),1); Par.r(1) = r; %Number of block factors
Par.p = 1; % Lags in the VAR on the factors
Par.nQ = 0; %n. of quarterly variables, it is necessary for the model to understand
the positions
lags=5;

```

```

Par.blocks = [Blockest];
Par.thresh = 1e-4;
Par.max_iter = 1000;

disp ('Estimation starts')
Res_in = EM_DFM_SS_block_idioQARMA_restrMQ(xin,Par);

clear Select_blocks TbegEst TendEst

disp ('Section 4: Estimation completed')

%% Section 5: Collect results
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
% Factor loadings
C = [Res_in.C(:,1:r) Res_in.C(:,r*lags+1:lags:(size(Par.blocks,2)+(r-1))*lags)];

% Global and block factors and idio
F_t = [Res_in.F(:,1:r) Res_in.F(:,r*lags+1:lags:(size(Par.blocks,2)+(r-1))*lags)];
e_t = Res_in.F(:,(lags*size(Par.blocks,2)+1:end));

% recalculate standard deviation and mean
Mx = nanmean(xin);
Sx = nanstd(xin);
xNaN = (xin-repmat(Mx,t,1))./repmat(Sx,t,1);

x_F= F_t*C';

for i=1:size(Par.blocks,2)
x_f(:, :, i)= F_t(:, i)*C(:, i)';
end

%% Cumulted factor
Cm_F_t=(cumsum(F_t(:,1)));
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%% Figure 6 Historical decomposition of commodity prices 2011-2019
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%

set(0, 'DefaultAxesTitleFontWeight', 'normal');

first_y = 2000; first_m = 1; %% Dates of the beginning of chart
chart_first = find((DatesEst(:,1)==first_y) & (DatesEst(:,3)==first_m));

last_y = 2008; last_m = 7; %% Dates of the end of the chart
chart_last = find((DatesEst(:,1)==last_y) & (DatesEst(:,3)==last_m));

% Define commodity prices to decompose
a = find(strcmp(Mnemest, 'Copper'));
b = find(strcmp(Mnemest, 'Brent Crude Oil'));
c = find(strcmp(Mnemest, 'Nickel'));
d = find(strcmp(Mnemest, 'Corn'));
e = find(strcmp(Mnemest, 'Gold '));

```

```

% The third dimension of x_f corresponds to which factor
% belong. EG. OIL is in: Global(1),Fuel(2),Oil(

oil_f = cumsum([x_f(chart_first:chart_last,b,1) x_f(chart_first:chart_last,b,2) x_f(
(chart_first:chart_last,b,4) e_t(chart_first:chart_last,b)];
oil_f = [oil_f(:,1) sum(oil_f(:,2:end-1),2) oil_f(:,end)]*Sx(b);

gold_f = cumsum([x_f(chart_first:chart_last,c,1) x_f(chart_first:chart_last,c,3) x_f(
(chart_first:chart_last,c,7) x_f(chart_first:chart_last,c,9) e_t(chart_first:
chart_last,c)];
gold_f = [gold_f(:,1) sum(gold_f(:,2:end-1),2) gold_f(:,end)]*Sx(c);

corn_f = cumsum([x_f(chart_first:chart_last,d,1) x_f(chart_first:chart_last,d,3) x_f(
(chart_first:chart_last,d,12) x_f(chart_first:chart_last,d,13) e_t(chart_first:
chart_last,d)];
corn_f = [corn_f(:,1) sum(corn_f(:,2:end-1),2) corn_f(:,end)]*Sx(d);

copper_f = cumsum([x_f(chart_first:chart_last,a,1) x_f(chart_first:chart_last,a,3)
x_f(chart_first:chart_last,a,7) x_f(chart_first:chart_last,a,9) e_t(chart_first:
chart_last,a)];
copper_f = [copper_f(:,1) sum(copper_f(:,2:end-1),2) copper_f(:,end)]*Sx(a);

%
%
time=(2000+1/12:1/12:2008+7/12)';
% OIL
figure
set(gcf,'PaperPosition',[0 0 10 14])
set(gcf,'papertype','A4letter');
subplot(4,1,1)
oil_pos = oil_f(1:end,:);
oil_pos(oil_pos>0) = 0;
oil_neg = oil_f(1:end,:);
oil_neg(oil_neg<0) = 0;
hold on
clear a b c d
%
a = bar(time,oil_pos,'stacked','EdgeColor','none');
set(a(1),'FaceColor','b')
set(a(2),'FaceColor','r')
set(a(3),'FaceColor',[0.5 0.5 0.5])
b = bar(time,oil_neg,'stacked','EdgeColor','none');
set(b(1),'FaceColor','b')
set(b(2),'FaceColor','r')
set(b(3),'FaceColor',[0.5 0.5 0.5])
plot(time, cumsum(xNaN(chart_first:chart_last,find(strcmp(Mnemest, 'Brent Crude
Oil'))))*Sx(find(strcmp(Mnemest, 'Brent Crude Oil'))),'k','LineWidth',2);
set(gca,'FontSize',12,'xlim',[2000 2008.7])
set(gca,'XTick',2000:24/12:2008.7)
set(gca,'XTickLabel',{'2000','2002','2004','2006','2008'})
title('Brent oil')
hold off
clear a b

```

```
% COPPER
subplot(4,1,2)
copper_pos = copper_f(1:end,:);
copper_pos(copper_pos>0) = 0;
copper_neg = copper_f(1:end,:);
copper_neg(copper_neg<0) = 0;
hold on
a = bar(time,copper_pos,'stacked','EdgeColor','none');
set(a(1),'FaceColor','b')
set(a(2),'FaceColor','r')
set(a(3),'FaceColor',[0.5 0.5 0.5])
b = bar(time,copper_neg,'stacked','EdgeColor','none');
set(b(1),'FaceColor','b')
set(b(2),'FaceColor','r')
set(b(3),'FaceColor',[0.5 0.5 0.5])
plot(time, cumsum(xNaN(chart_first:chart_last,find(strcmp(Mnemest, 'Copper'))))*Sx
(find(strcmp(Mnemest, 'Copper'))),'k','LineWidth',2);
set(gca,'FontSize',12,'xlim',[2000 2008.7])
set(gca,'XTick',2000:24/12:2008.7)
set(gca,'XTickLabel',{'2000','2002','2004','2006','2008'})
title('Copper')
hold off
clear a b

% CORN
subplot(4,1,3)
corn_pos = corn_f(1:end,:);
corn_pos(corn_pos>0) = 0;
corn_neg = corn_f(1:end,:);
corn_neg(corn_neg<0) = 0;
hold on
a = bar(time,corn_pos,'stacked','EdgeColor','none');
set(a(1),'FaceColor','b')
set(a(2),'FaceColor','r')
set(a(3),'FaceColor',[0.5 0.5 0.5])
b = bar(time,corn_neg,'stacked','EdgeColor','none');
set(b(1),'FaceColor','b')
set(b(2),'FaceColor','r')
set(b(3),'FaceColor',[0.5 0.5 0.5])
plot(time, cumsum(xNaN(chart_first:chart_last,find(strcmp(Mnemest, 'Corn'))))*Sx
(find(strcmp(Mnemest, 'Corn'))),'k','LineWidth',2);
set(gca,'FontSize',12,'xlim',[2000 2008.7])
set(gca,'XTick',2000:24/12:2008.7)
set(gca,'XTickLabel',{'2000','2002','2004','2006','2008'})
title('Corn (Maize)')
hold off
clear a b

%
subplot(4,1,4)
gold_pos = gold_f(1:end,:);
gold_pos(gold_pos>0) = 0;
gold_neg = gold_f(1:end,:);
gold_neg(gold_neg<0) = 0;
```

```

hold on
a = bar(time, gold_pos, 'stacked', 'EdgeColor', 'none');
set(a(1), 'FaceColor', 'b')
set(a(2), 'FaceColor', 'r')
set(a(3), 'FaceColor', [0.5 0.5 0.5])
b = bar(time, gold_neg, 'stacked', 'EdgeColor', 'none');
set(b(1), 'FaceColor', 'b')
set(b(2), 'FaceColor', 'r')
set(b(3), 'FaceColor', [0.5 0.5 0.5])
plot(time, cumsum(xNaN(chart_first:chart_last, find(strcmp(Mnemest, 'Nickel'))))*Sx(
(find(strcmp(Mnemest, 'Nickel'))), 'k', 'LineWidth', 2);

legend([a,b], {'Global factor', 'Block
factors', 'Idiosyncratic'}, 'Location', 'Best', 'FontSize', 7);
legend('boxoff')
set(gca, 'FontSize', 12, 'xlim', [2000 2008.7])
set(gca, 'XTick', 2000:24/12:2008.7)
set(gca, 'XTickLabel', {'2000', '2002', '2004', '2006', '2008'})
title('Nickel')
hold off
clear a b
%
filename = fullfile(output, '2012-2018 hist dec');
savefig(filename);
print(filename, '-djpeg');

%% gold
first_y = 2000; first_m = 1; %% Dates of the beginning of chart
chart_first = find((DatesEst(:,1)==first_y) & (DatesEst(:,3)==first_m));

last_y = 2014; last_m = 1; %% Dates of the end of the chart
chart_last = find((DatesEst(:,1)==last_y) & (DatesEst(:,3)==last_m));

% Define commodity prices to decompose
e = find(strcmp(Mnemest, 'Gold '));

pm_f = cumsum([x_f(chart_first:chart_last,e,1) x_f(chart_first:chart_last,e,3) x_f(
(chart_first:chart_last,e,7) x_f(chart_first:chart_last,e,10) e_t(chart_first:
chart_last,e)]);
pm_f = [pm_f(:,1) sum(pm_f(:,2:end-1),2) pm_f(:,end)]*Sx(e);

time=(2000+1/12:1/12:2014+1/12)';

figure
pm_pos = pm_f(1:end,:);
pm_pos(pm_pos>0) = 0;
pm_neg = pm_f(1:end,:);
pm_neg(pm_neg<0) = 0;
hold on
a = bar(time, pm_pos, 'stacked', 'EdgeColor', 'none');
set(a(1), 'FaceColor', 'b')
set(a(2), 'FaceColor', 'r')
set(a(3), 'FaceColor', [0.5 0.5 0.5])
b = bar(time, pm_neg, 'stacked', 'EdgeColor', 'none');

```

```

set(b(1),'FaceColor','b')
set(b(2),'FaceColor','r')
set(b(3),'FaceColor',[0.5 0.5 0.5])
plot(time, cumsum(xNaN(chart_first:chart_last,find(strcmp(Mnemest, 'Gold '))))*Sx(
(find(strcmp(Mnemest, 'Gold '))), 'k', 'LineWidth', 2);
%set(gca,'FontSize',12,'xlim',[2000 2014.1])
set(gca,'XTick',2000:24/12:2014.1)
set(gca,'XTickLabel',{'2000','2002','2004','2006','2008','2010','2012','2014'})
title('Gold')
hold off
clear a b

filename = fullfile(output, '2012-2018 GOLD');
savefig(filename);
print(filename, '-djpeg');

%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
% Figure 7 Historical decomposition of oil prices
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
oil = find(strcmp(Mnemest, 'Brent Crude Oil'));

figure
reset(gcf)
set(gcf,'papertype','A4letter');
set(gcf,'PaperPosition',[0 0 15 12])
% 2. Gulf war 90-91
first_y = 1990; first_m = 7;
chart_first = find((DatesEst(:,1)==first_y) & (DatesEst(:,3)==first_m));
last_y = 1991; last_m = 3;
chart_last = find((DatesEst(:,1)==last_y) & (DatesEst(:,3)==last_m));
time=(1990+7/12:1/12:1991+3/12)';

subplot(2,2,1)
oil_f = cumsum([x_f(chart_first:chart_last,oil,1) x_f(chart_first:chart_last,oil,2)
x_f(chart_first:chart_last,oil,4) e_t(chart_first:chart_last,oil)]);
oil_f = [oil_f(:,1) sum(oil_f(:,2:end-1),2) oil_f(:,end)]*Sx(oil);
oil_pos = oil_f;
oil_pos(oil_pos>0) = 0;
oil_neg = oil_f;
oil_neg(oil_neg<0) = 0;
hold on
a = bar(oil_pos,'stacked','EdgeColor','none','BarWidth',0.6);
set(a(1),'FaceColor','b')
set(a(2),'FaceColor','r')
set(a(3),'FaceColor',[0.5 0.5 0.5])
b = bar(oil_neg,'stacked','EdgeColor','none','BarWidth',0.6);
set(b(1),'FaceColor','b')
set(b(2),'FaceColor','r')
set(b(3),'FaceColor',[0.5 0.5 0.5])
plot(cumsum(xNaN(chart_first:chart_last,oil))*Sx(oil),'k','LineWidth',3);
set(gca,'FontSize',12,'XTick',1:4:10)
set(gca,'XTickLabel',{'07/90','11/90','03/91'})
set(gca,'XTickLabelRotation',50)
title('The Gulf War', 'July 1990 - March 1991')

```

```

hold off
clear oil_f oil_pos oil_neg

% 3. Great recession 2008-2009
first_y = 2008; first_m = 8;
chart_first = find((DatesEst(:,1)==first_y) & (DatesEst(:,3)==first_m));
last_y = 2009; last_m = 2;
chart_last = find((DatesEst(:,1)==last_y) & (DatesEst(:,3)==last_m));

time=(2008+8/12:1/12:2009+2/12)';

subplot(2,2,2)

oil_f = cumsum([x_f(chart_first:chart_last,oil,1) x_f(chart_first:chart_last,oil,2)
x_f(chart_first:chart_last,oil,4) e_t(chart_first:chart_last,oil)]);
oil_f = [oil_f(:,1) sum(oil_f(:,2:end-1),2) oil_f(:,end)]*Sx(oil);

oil_pos = oil_f;
oil_pos(oil_pos>0) = 0;
oil_neg = oil_f;
oil_neg(oil_neg<0) = 0;
hold on
a = bar(oil_pos,'stacked','EdgeColor','none','BarWidth',0.6);
set(a(1),'FaceColor','b')
set(a(2),'FaceColor','r')
set(a(3),'FaceColor',[0.5 0.5 0.5])
b = bar(oil_neg,'stacked','EdgeColor','none','BarWidth',0.6);
set(b(1),'FaceColor','b')
set(b(2),'FaceColor','r')
set(b(3),'FaceColor',[0.5 0.5 0.5])
plot(cumsum(xNaN(chart_first:chart_last,oil))*Sx(oil),'k','LineWidth',3);
set(gca,'FontSize',12,'XTick',1:3:7)
set(gca,'XTickLabel',{'08/08','12/08','02/09'})
%set(gca,'XTickLabelRotation',50)
xlim([0 8])
ylim([-150 50])
title('The Great Recession', '08/2008 - 02/2009')
set(gcf,'Position',[10 10 500 500])
hold off
clear oil_f oil_pos oil_neg a b

% 4. The oil price fall in 2014
first_y = 2014; first_m = 7;
chart_first = find((DatesEst(:,1)==first_y) & (DatesEst(:,3)==first_m));
last_y = 2015; last_m = 12;
chart_last = find((DatesEst(:,1)==last_y) & (DatesEst(:,3)==last_m));

oil_f = cumsum([x_f(chart_first:chart_last,oil,1) x_f(chart_first:chart_last,oil,2)
x_f(chart_first:chart_last,oil,4) e_t(chart_first:chart_last,oil)]);
oil_f = [oil_f(:,1) sum(oil_f(:,2:end-1),2) oil_f(:,end)]*Sx(oil);
oil_pos = oil_f;
oil_pos(oil_pos>0) = 0;
oil_neg = oil_f;
oil_neg(oil_neg<0) = 0;

```



```

subplot(2,2,3)
a = bar(oil_pos, 'stacked', 'EdgeColor', 'none', 'BarWidth', 0.8);
set(a(1), 'FaceColor', 'b')
set(a(2), 'FaceColor', 'r')
set(a(3), 'FaceColor', [0.5 0.5 0.5])
hold on
b = bar(oil_neg, 'stacked', 'EdgeColor', 'none', 'BarWidth', 0.8);
set(b(1), 'FaceColor', 'b')
set(b(2), 'FaceColor', 'r')
set(b(3), 'FaceColor', [0.5 0.5 0.5])
plot(cumsum(xNaN(chart_first:chart_last,oil))*Sx(oil), 'k', 'LineWidth', 3);
xlim([1 14])
ylim([-150 50])
% 2014.7::2008.7
% legend([a,b], {'Global factor', 'Block
factors', 'Idiosyncratic'}, 'Location', 'Best', 'FontSize', 9);
% legend('boxoff')
set(gca, 'FontSize', 12, 'XTick', 1:3:18)
set(gca, 'XTickLabel', {'07/14', '11/14', '03/15', '07/15', '11/15'})
%set(gca, 'XTickLabelRotation', 50)
title('The oil price fall', '2014 - 2015')
set(gcf, 'Position', [10 10 500 500])
hold off
clear oil_f oil_pos oil_neg a b

% 5. COVID-19 crisis
first_y = 2020; first_m = 1;
chart_first = find((DatesEst(:,1)==first_y) & (DatesEst(:,3)==first_m));
last_y = 2021; last_m = 1;
chart_last = find((DatesEst(:,1)==last_y) & (DatesEst(:,3)==last_m));

oil_f = cumsum([x_f(chart_first:chart_last,oil,1) x_f(chart_first:chart_last,oil,2)
x_f(chart_first:chart_last,oil,4) e_t(chart_first:chart_last,oil)]);
oil_f = [oil_f(:,1) sum(oil_f(:,2:end-1),2) oil_f(:,end)]*Sx(oil);
oil_pos = oil_f;
oil_pos(oil_pos>0) = 0;
oil_neg = oil_f;
oil_neg(oil_neg<0) = 0;

subplot(2,2,4)
a = bar(oil_pos, 'stacked', 'EdgeColor', 'none', 'BarWidth', 0.8);
set(a(1), 'FaceColor', 'b')
set(a(2), 'FaceColor', 'r')
set(a(3), 'FaceColor', [0.5 0.5 0.5])
hold on
b = bar(oil_neg, 'stacked', 'EdgeColor', 'none', 'BarWidth', 0.8);
set(b(1), 'FaceColor', 'b')
set(b(2), 'FaceColor', 'r')
set(b(3), 'FaceColor', [0.5 0.5 0.5])
plot(cumsum(xNaN(chart_first:chart_last,oil))*Sx(oil), 'k', 'LineWidth', 3);
xlim([1 19])
ylim([-150 50])
legend([a,b], {'Global factor', 'Block

```

```
factors','Idiosyncratic'},'Location','Best','FontSize',7);
legend('boxoff')
set(gcf,'Position',[10 10 500 500])
set(gca,'FontSize',12,'XTick',1:2:13)
set(gca,'XTickLabel',{'01/20',' ','05/20',' ','09/20',' ','01/21'})
%set(gca,'XTickLabelRotation',50)
title('COVID-19','01/20 - 01/21')
hold off
clear oil_f oil_pos oil_neg a b

filename = fullfile(output, 'Cases on oil price');
savefig(filename);
print(filename, '-djpeg');

%% L_S_TEST: model based variance decomposition:

% Sigma_y=W*delta*Sigma_f*Delta'*W'+W*Sigma_e*W'

% weights is mxn matrix, m=number of indeces, n=variables
% delta are factor loadings
% sigma_f and sigma_e are the variance-covariance matrices of factor and
% idiosyncratic error

% Sigma_y=w'*C*cov(F_t)*C'*w+w'*cov(e_t)*w ;
%
% y_t=Res_in.X_sm*w ;
%
% SigmaE =inv(w'*C/cov(F_t)*C'*w);
%
%
% SigmaYe =zeros(14,1); %variance of Y due to identified shock
% SigmaYe =SigmaYe +diag(C*SigmaE*C');
%
% SigmaY =zeros(14,1); %total forecast error variance of Y
% SigmaY=SigmaY+diag(Sigma_y);
```

```

%%% Replication files for:
%%% "'Nowcasting", 2010, (by Marta Banbura, Domenico Giannone and Lucrezia✓
Reichlin),
%%% in Michael P. Clements and David F. Hendry, editors, Oxford Handbook on Economic✓
Forecasting.
%%%
%%% The software can be freely used in applications.
%%% Users are kindly requested to add acknowledgements to published work and
%%% to cite the above reference in any resulting publications
function Res = EM_DFM_SS_block_idioQARMA_restrMQ(X,Par,Res_old)

nQ = Par.nQ;

nM = size(X,2)-nQ;

thresh = Par.thresh;
r = Par.r;
p = Par.p;
max_iter = Par.max_iter;

i_idio = logical([ones(nM,1);zeros(nQ,1)]);

R_mat = [2 -1 0 0 0;...
          3 0 -1 0 0;...
          2 0 0 -1 0;...
          1 0 0 0 -1]; % matrix of constraints on the loading of quarterly data

q = zeros(4,1);

blocks = Par.blocks;

%-----
% Preparation of the data
%-----
[T,N] = size(X);

if nargin<3
    % Standardise x
    Mx = nanmean(X);
    Wx = (nanstd(X));

else
    Mx = Res_old.Mx;
    Wx = Res_old.Wx;
end

xNaN = (X-repmat(Mx,T,1))./repmat(Wx,T,1);

%-----
% Initial Conditions
%-----

```

```

%Removing missing values (for initial estimators)
optNaN.method = 2; % Remove leading and closing zeros
optNaN.k = 3;

if nargin<3
    [A, C, Q, R, Z_0, V_0] = InitCond(xNaN,r,p,blocks,optNaN,R_mat,q,nQ,i_idio);
else
    A = Res_old.A;
    C = Res_old.C;
    Q = Res_old.Q;
    R = Res_old.R;
    Z_0 = Res_old.Z_0;
    V_0 = Res_old.V_0;
end;

% some auxiliary variables for the iterations
previous_loglik = -inf;
num_iter = 0;
LL = -inf;
converged = 0;

% y for the estimation is WITH missing data
y = xNaN';

%-----
%THE EM LOOP
%-----

%The model can be written as
%y = C*Z + e;
%Z = A*Z(-1) + v
%where y is NxT, Z is (pr)xT, etc

%remove the leading and ending nans for the estimation
optNaN.method = 3;
y_est = remNaNs_spline(xNaN,optNaN)';

while (num_iter < max_iter) & ~converged
    [C_new, R_new, A_new, Q_new, Z_0, V_0, loglik] = ...
        EMstep(y_est, A, C, Q, R, Z_0, V_0, r,p,R_mat,q,nQ,i_idio,blocks);

    C = C_new;
    R = R_new;
    A = A_new;
    Q = Q_new;

    % Checking convergence
    if num_iter>2
        [converged,decrease(num_iter+1)] = em_converged(loglik, previous_loglik, thresh,
1);
    end
end

```

```

LL = [LL loglik];
previous_loglik = loglik;
num_iter = num_iter + 1;

if mod(num_iter,10)==0
    disp(['Now Running the ',num2str(num_iter),'th Iteration'])
    disp(diff(LL(end-1:end))/mean(LL(end-1:end))*200)
end
end

%final run of the Kalman filter
%-----
Zsmooth = runKF(y, A, C, Q, R, Z_0, V_0)';
x_sm = Zsmooth(2:end,:)*C';

Res.X_sm = repmat(Wx,T,1).*x_sm+repmat(Mx,T,1);
Res.F = Zsmooth(2:end,:);

%-----
% Loading the structure with the results
%-----
Res.C = C;
Res.R = R;
Res.A = A;
Res.Q = Q;
Res.Mx = Mx;
Res.Wx = Wx;
Res.Z_0 = Z_0;
Res.V_0 = V_0;
Res.r = r;
Res.p = p;
Res.L = loglik;

%-----
%PROCEDURES
%-----

function [C_new, R_new, A_new, Q_new, Z_0, V_0, loglik] = EMstep(y, A, C, Q, R, Z_0, V_0, r,p,R_mat,q,nQ,i_idio,blocks)

[n,T] = size(y);
nM = n-nQ;

pC = size(R_mat,2);
ppC = max(p,pC);

n_b = size(blocks,2);

% Compute the (expected) sufficient statistics for a single Kalman filter sequence.

%Running the Kalman filter with the current estimates of the parameters

```

```

[Zsmooth, Vsmooth, VVsmooth, loglik] = runKF(y, A, C, Q, R, Z_0, V_0);

A_new = A;
Q_new = Q;
V_0_new = V_0;

for i = 1:n_b
    r_i = r(i);
    rp = r_i*p;
    rp1 = sum(r(1:i-1))*ppC;

    A_i = A(rp1+1:rp1+r_i*ppC, rp1+1:rp1+r_i*ppC);
    Q_i = Q(rp1+1:rp1+r_i*ppC, rp1+1:rp1+r_i*ppC);

    EZZ = Zsmooth(rp1+1:rp1+rp, 2:end)*Zsmooth(rp1+1:rp1+rp, 2:end)'...
        +sum(Vsmooth(rp1+1:rp1+rp, rp1+1:rp1+rp, 2:end), 3); %E↵
    (Z'Z)
    EZZ_BB = Zsmooth(rp1+1:rp1+rp, 1:end-1)*Zsmooth(rp1+1:rp1+rp, 1:end-1)'...
        +sum(Vsmooth(rp1+1:rp1+rp, rp1+1:rp1+rp, 1:end-1), 3); %E(Z(-1)'Z_(-1))
    EZZ_FB = Zsmooth(rp1+1:rp1+rp, 2:end)*Zsmooth(rp1+1:rp1+rp, 1:end-1)'...
        +sum(VVsmooth(rp1+1:rp1+rp, rp1+1:rp1+rp, :), 3); %E(Z'Z_(-1))

    A_i(1:r_i, 1:rp) = EZZ_FB(1:r_i, 1:rp) * inv(EZZ_BB(1:rp, 1:rp));
    Q_i(1:r_i, 1:r_i) = (EZZ(1:r_i, 1:r_i) - A_i(1:r_i, 1:rp)*EZZ_FB(1:r_i, 1:rp)') / T;↵
%d

    A_new(rp1+1:rp1+r_i*ppC, rp1+1:rp1+r_i*ppC) = A_i;
    Q_new(rp1+1:rp1+r_i*ppC, rp1+1:rp1+r_i*ppC) = Q_i;
    V_0_new(rp1+1:rp1+r_i*ppC, rp1+1:rp1+r_i*ppC) = Vsmooth(rp1+1:rp1+r_i*ppC, rp1+1:↵
rp1+r_i*ppC, 1);
end

rp1 = sum(r)*ppC;
niM = sum(i_idio(1:nM));
% idiosyncratic
EZZ = diag(diag(Zsmooth(rp1+1:end, 2:end)*Zsmooth(rp1+1:end, 2:end)'))...
    +diag(diag(sum(Vsmooth(rp1+1:end, rp1+1:end, 2:end), 3))); %E↵
E(Z'Z)
EZZ_BB = diag(diag(Zsmooth(rp1+1:end, 1:end-1)*Zsmooth(rp1+1:end, 1:end-1)'))...
    +diag(diag(sum(Vsmooth(rp1+1:end, rp1+1:end, 1:end-1), 3))); %E(Z(-1)'Z_(-1))
EZZ_FB = diag(diag(Zsmooth(rp1+1:end, 2:end)*Zsmooth(rp1+1:end, 1:end-1)'))...
    +diag(diag(sum(VVsmooth(rp1+1:end, rp1+1:end, :), 3))); %E(Z'Z_(-1))

A_i = EZZ_FB * diag(1./diag((EZZ_BB)));
Q_i = (EZZ - A_i*EZZ_FB') / T;

A_new(rp1+1:rp1+niM, rp1+1:rp1+niM) = A_i(1:niM, 1:niM);
Q_new(rp1+1:rp1+niM, rp1+1:rp1+niM) = Q_i(1:niM, 1:niM);
V_0_new(rp1+1:rp1+niM, rp1+1:rp1+niM) = diag(diag(Vsmooth(rp1+1:rp1+niM, rp1+1:↵
rp1+niM, 1)));

Z_0 = Zsmooth(:, 1); %zeros(size(Zsmooth, 1), 1); %

```

```

nanY = isnan(y);
y(nanY) = 0;

% LOADINGS
C_new = C;

% Blocks
bl = unique(blocks, 'rows');
n_bl = size(bl,1);
bl_idxM = [];
bl_idxQ = [];
R_con = [];
q_con = [];
for i = 1:n_b
    bl_idxQ = [bl_idxQ repmat(bl(:,i),1,r(i)*ppC)];
    bl_idxM = [bl_idxM repmat(bl(:,i),1,r(i)) zeros(n_bl,r(i)*(ppC-1))];
    R_con = blkdiag(R_con, kron(R_mat,eye(r(i))));
    q_con = [q_con;zeros(r(i)*size(R_mat,1),1)];
end

bl_idxM = logical(bl_idxM);
bl_idxQ = logical(bl_idxQ);

%idio
i_idio_M = i_idio(1:nM);
n_idio_M = length(find(i_idio_M));
c_i_idio = cumsum(i_idio);

for i = 1:n_bl
    bl_i = bl(i,:);
    rs = sum(r(logical(bl_i)));
    idx_i = find(ismember(blocks,bl_i,'rows'));

    % MONTHLY
    idx_iM = idx_i(idx_i<nM+1);
    n_i = length(idx_iM);

    denom = zeros(n_i*rs,n_i*rs);
    nom = zeros(n_i,rs);

    i_idio_i = i_idio_M(idx_iM);
    i_idio_ii = c_i_idio(idx_iM);
    i_idio_ii = i_idio_ii(i_idio_i);
    for t=1:T
        nanYt = diag(~nanY(idx_iM,t));
        denom = denom + kron(Zsmooth(bl_idxM(i,:),t+1)*Zsmooth(bl_idxM(i,:),t+1)'.
            +Vsmooth(bl_idxM(i,:),bl_idxM(i,:),t+1),nanYt);
        nom = nom + y(idx_iM,t)*Zsmooth(bl_idxM(i,:),t+1)'.
modification
        -nanYt(:,i_idio_i)*(Zsmooth(rp1+i_idio_ii,t+1)*Zsmooth(bl_idxM(i,:),
t+1)'.
            +Vsmooth(rp1+i_idio_ii,bl_idxM(i,:),t+1));
    end
    vec_C = inv(denom)*nom(:);

```

```

C_new(idx_iM,bl_idxM(i,:)) = reshape(vec_C,n_i,rs);

% QUARTERLY
idx_iQ = idx_i(idx_i>nM);
rps = rs*ppC;

R_con_i = R_con(:,bl_idxQ(i,:));
q_con_i = q_con;
no_c = ~(any(R_con_i,2));
R_con_i(no_c,:) = [];
q_con_i(no_c,:) = [];

for j = idx_iQ'
    denom = zeros(rps,rps);
    nom = zeros(1,rps);
    idx_jQ = j-nM;
    i_idio_jQ = (rp1+n_idio_M+5*(idx_jQ-1)+1:rp1+n_idio_M+5*idx_jQ);
    V_0_new(i_idio_jQ,i_idio_jQ) = Vsmooth(i_idio_jQ,i_idio_jQ,1);
    A_new(i_idio_jQ(1),i_idio_jQ(1)) = A_i(i_idio_jQ(1)-rp1,i_idio_jQ(1)-rp1);
    Q_new(i_idio_jQ(1),i_idio_jQ(1)) = Q_i(i_idio_jQ(1)-rp1,i_idio_jQ(1)-rp1);

    for t=1:T
        nanYt = diag(~nanY(j,t));
        denom = denom + kron(Zsmooth(bl_idxQ(i,:),t+1)*Zsmooth(bl_idxQ(i,:),
t+1)'+...
            +Vsmooth(bl_idxQ(i,:),bl_idxQ(i,:),t+1),nanYt);
        nom = nom + y(j,t)*Zsmooth(bl_idxQ(i,:),t+1)';
        nom = nom -...
            nanYt*([1 2 3 2 1]*Zsmooth(i_idio_jQ,t+1)*Zsmooth(bl_idxQ(i,:),
t+1)'+...
            [1 2 3 2 1]*Vsmooth(i_idio_jQ,bl_idxQ(i,:),t+1));

    end

    C_i = inv(denom)*nom';
    C_i_constr = C_i - inv(denom)*R_con_i'*inv(R_con_i*inv(denom)*R_con_i')*
(R_con_i*C_i-q_con_i);
    C_new(j,bl_idxQ(i,:)) = C_i_constr;

end

end

R_new = zeros(n,n);
for t=1:T
    nanYt = diag(~nanY(:,t));
    R_new = R_new + (y(:,t)-nanYt*C_new*Zsmooth(:,t+1))*(y(:,t)-nanYt*C_new*Zsmooth
(:,t+1))'+...
        +nanYt*C_new*Vsmooth(:,t+1)*C_new'*nanYt...
        +(eye(n)-nanYt)*R*(eye(n)-nanYt);
end

```



```

R_new = R_new/T;
RR = diag(R_new); %RR(RR<1e-2) = 1e-2;
RR(i_idio_M) = 1e-04;
RR(nM+1:end) = 1e-04;
R_new = diag(RR);

%-----

function [converged, decrease] = em_converged(loglik, previous_loglik, threshold,
check_increased)
% EM_CONVERGED Has EM converged?
% [converged, decrease] = em_converged(loglik, previous_loglik, threshold)
%
% We have converged if the slope of the log-likelihood function falls below
'threshold',
% i.e.,  $|f(t) - f(t-1)| / \text{avg} < \text{threshold}$ ,
% where  $\text{avg} = (|f(t)| + |f(t-1)|)/2$  and  $f(t)$  is log lik at iteration t.
% 'threshold' defaults to 1e-4.
%
% This stopping criterion is from Numerical Recipes in C p423
%
% If we are doing MAP estimation (using priors), the likelihood can decrease,
% even though the mode of the posterior is increasing.

if nargin < 3, threshold = 1e-4; end
if nargin < 4, check_increased = 1; end

converged = 0;
decrease = 0;

if check_increased
    if loglik - previous_loglik < -1e-3 % allow for a little imprecision
        fprintf(1, '*****likelihood decreased from %6.4f to %6.4f!\n',
previous_loglik, loglik);
        decrease = 1;
    end
end

delta_loglik = abs(loglik - previous_loglik);
avg_loglik = (abs(loglik) + abs(previous_loglik) + eps)/2;
if (delta_loglik / avg_loglik) < threshold, converged = 1; end

%-----

function [ A, C, Q, R, initZ, initV] = InitCond(x,r,p,blocks,optNaN,Rcon,q,NQ,
i_idio)

pC = size(Rcon,2);
ppC = max(p,pC);

```

```

n_b = size(blocks,2);

OPTS.disp=0;

[xBal,indNaN] = remNaNs_spline(x,optNaN);
[T,N] = size(xBal);
NM = N-NQ;

xNaN = xBal;
xNaN(indNaN) = nan;
C = [];
A = [];
Q = [];
initV = [];

res = xBal;
resNaN = xNaN;
indNaN(1:pC-1,:) = true;
for i = 1:n_b
    r_i = r(i);
    %-----
    % Observation equation
    %-----
    C_i = zeros(N,r_i*ppC);
    idx_i = find(blocks(:,i));
    idx_iM = idx_i(idx_i<NM+1);
    idx_iQ = idx_i(idx_i>NM);
    [v,d] = eigs(cov(res(:,idx_iM)),r_i,'lm',OPTS);
    C_i(idx_iM,1:r_i) = v;
    f = res(:,idx_iM)*v;
    F = [];
    for kk = 0:max(p+1,pC)-1
        F = [F f(pC-kk:end-kk,:)];
    end
    Rcon_i = kron(Rcon,eye(r_i));
    q_i = kron(q,zeros(r_i,1));
    ff = F(:,1:r_i*pC);
    for j = idx_iQ'
        xx_j = resNaN(pC:end,j);
        if sum(~isnan(xx_j)) < size(ff,2)+2
            xx_j = res(pC:end,j);
        end
        ff_j = ff(~isnan(xx_j),:);
        xx_j = xx_j(~isnan(xx_j));
        iff_j = inv(ff_j'*ff_j);
        Cc = iff_j*ff_j'*xx_j;
        Cc = Cc - iff_j*Rcon_i'*inv(Rcon_i*iff_j*Rcon_i')*(Rcon_i*Cc-q_i);
        C_i(j,1:pC*r_i)=Cc';
    end
    ff = [zeros(pC-1,pC*r_i);ff];
    res = res - ff*C_i';
    resNaN = res;
    resNaN(indNaN) = nan;
    C = [C C_i];

```

```

%-----
% Transition equation
%-----
z = F(:,1:r_i);
Z = F(:,r_i+1:r_i*(p+1));
A_i = zeros(r_i*ppC,r_i*ppC)';
A_temp = inv(Z'*Z)*Z'*z;
A_i(1:r_i,1:r_i*p) = A_temp';
A_i(r_i+1:end,1:r_i*(ppC-1)) = eye(r_i*(ppC-1));

%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
Q_i = zeros(ppC*r_i,ppC*r_i);
e = z - Z*A_temp;          % VAR residuals
Q_i(1:r_i,1:r_i) = cov(e); % VAR covariance matrix

initV_i = reshape(inv(eye((r_i*ppC)^2)-kron(A_i,A_i))*Q_i(:,r_i*ppC,r_i*ppC);

A = blkdiag(A,A_i);
Q = blkdiag(Q,Q_i);
initV = blkdiag(initV,initV_i);

end

R = diag(nanvar(resNaN));

eyeN = eye(N);
eyeN(:,~i_idio) = [];
% Initial conditions
C=[C eyeN];

ii_idio = find(i_idio);
n_idio = length(ii_idio);
B = zeros(n_idio);
S = zeros(n_idio);

for i = 1:n_idio;
    R(ii_idio(i),ii_idio(i)) = 1e-04;

    res_i = resNaN(:,ii_idio(i));
    % number of leading zeros
    leadZero = max( find( (1:T)' == cumsum(isnan(res_i)) ) );
    endZero = max( find( (1:T)' == cumsum(isnan(res_i(end:-1:1))) ) );

    res_i = res(:,ii_idio(i));
    res_i(end-endZero:endZero) = [];
    res_i(1:leadZero) = [];

    BM(i,i) = inv(res_i(1:end-1)'*res_i(1:end-1))*res_i(1:end-1)'*res_i(2:end,:);
    SM(i,i) = cov(res_i(2:end)-res_i(1:end-1)*B(i,i));
end
initViM = diag(1./diag(eye(size(BM,1))-BM.^2)).*SM;

```

```
C = [C [zeros(NM,5*NQ);kron(eye(NQ),[1 2 3 2 1])]];
Rdiag = diag(R);
sig_e = Rdiag(NM+1:N)/19;
Rdiag(NM+1:N) = 1e-04;
R = diag(Rdiag);

rho0 = 0.1;
BQ = kron(eye(NQ),[[rho0 zeros(1,4)];[eye(4),zeros(4,1)]]);
temp = zeros(5);
temp(1,1) = 1;
SQ = kron(diag((1-rho0^2)*sig_e),temp);

%initViQ = eye((5*NQ));
initViQ = reshape(inv(eye((5*NQ)^2)-kron(BQ,BQ))*SQ(:),5*NQ,5*NQ);

A = blkdiag(A, BM, BQ);
Q = blkdiag(Q, SM, SQ);

% Initial conditions
initZ = zeros(size(A,1),1);
initV = blkdiag(initV, initViM, initViQ);
```

```
%% first var

clear;close all; clc

cd 'C:\Users\Leonardo\Google
Drive\1_UNIPD\16_THESIS\Thesis\Final_results\results\1992-2019'

%loading data

[DATA,TEXT]= xlsread('C:\Users\Leonardo\Google
Drive\1_UNIPD\16_THESIS\Thesis\Final_results\Data\data.xlsx','DATA');

dates=datevec(TEXT(2:end,1))

%Estimation sample

BegEstY = 1992; BegEstM = 7; %07/1992
EndEstY = 2019; EndEstM = 4;

TbegEst = find(dates(:,1)==BegEstY & dates(:,3)==BegEstM);
TendEst = find(dates(:,1)==EndEstY & dates(:,3)==EndEstM);

X=DATA(TbegEst:TendEst,:);

VAR_ALL_NAMES=TEXT(1,2:end)

%VARIABLES TO LOG

LOG_V={'CPI','WIP','INDPRO','EURO_INDPRO','HCPI_EURO'};

logTransform=ismember(VAR_ALL_NAMES,LOG_V);

X(:,logTransform)=log(X(:,logTransform))*100;

%Variables In the Var

N_CCF = (X(:,1));
R_CCF = X(:,2);
CPI = X(:,3);
INDPRO = X(:,4);
WIP = X(:,5);
GFU = X(:,6);
GFC = X(:,7);
FEDFUNDS = X(:,8);
S_FUNDS = X(:,9);
R_CCF_yoy = normalize(X(:,10));
R_CCF_cumsum_noinitial = normalize(X(:,11));
R_CCF_cumsum = normalize(X(:,12));
EURO_INDPRO = X(:,13);
HCPI_EURO = X(:,14);
EURO_RATE = X(:,15);

SHORT_NAME={'GFU','GFC','WIP','R_CCF','INDPRO','CPI','S_FUNDS',...
```

```
}
LONG_NAME={'Global Financial Uncertainty', 'Global Financial Cycle',...
          'World Industrial Production', 'Common Commodity Factor', ...
          'USA Industrial Production', 'Consumer Price Index', 'Federal Funds Rate',...
          }

SVAR=[GFU GFC WIP R_CCF_cumsum INDPRO CPI S_FUNDS]

%% SVAR
% Choose constant and trend
const_trend = 2;

% Choose number of lags
nbr_lags = 12;

% model
[VAR, VARopt] = VARmodel(SVAR,nbr_lags,const_trend);

% OPTIONS

%Vnames
VARopt.vnames = LONG_NAME;

% number of steps for computation of IRFs and FEVDs
VARopt.nsteps = 48;

% number of bootstrap for sign restriction and else
VARopt.ndraws = 1000;

% size of the shock for IRFs: 0=1stdev, 1=unit shock
VARopt.impact = 0;

%title on top
VARopt.suptitle = 2;

VARopt.sr_hor = 0;

%frequency
VARopt.frequency = 'm';

% Choose identification model
VARopt.ident = 'short';

% method for computation of recursive stuff ('wold' form MA representation, 'comp'
for companion form)
VARopt.recurs = 'wold';

% confidence level for bootstrap, default = 95
VARopt.pctg = 68;

% name of the shocks
VARopt.snames = VARopt.vnames;

%select on variable to plot, if=0 plot all
```

```
VARopt.pick = 0;

%printing
[TABLE_VAR, beta] = VARprint(VAR,VARopt);

% bootstrap method
VARopt.method = 'bs';

% IR
[IRF,VAR] = VARir(VAR,VARopt);

% BANDS
[IRF_lower,IRF_upper,IRF_median,IRF_mean] = VARirband(VAR,VARopt);

% Plot impulse response functions
VARirplot_(IRF_mean,VARopt,IRF_lower,IRF_upper);

% VD
% Compute forecast error variance decompositions (VDs) for the VAR model
[VD92, VAR] = VARvd(VAR,VARopt);

% Computing confidence intervals
[vd_INF,vd_SUP,vd_MED,vd_BAR] = VARvdband(VAR,VARopt);

%% SECOND var

clearvars -except VD92

cd 'C:\Users\Leonardo\Google
Drive\1_UNIPD\16_THESIS\Thesis\Final_results\results\2003-2019'

%loading data

[DATA,TEXT]= xlsread('C:\Users\Leonardo\Google
Drive\1_UNIPD\16_THESIS\Thesis\Final_results\Data\data.xlsx', 'DATA');

dates=datevec(TEXT(2:end,1))

%Estimation sample

BegEstY = 2003; BegEstM = 8; %07/1992
EndEstY = 2019; EndEstM = 4;

TbegEst = find(dates(:,1)==BegEstY & dates(:,3)==BegEstM);
TendEst = find(dates(:,1)==EndEstY & dates(:,3)==EndEstM);

X=DATA(TbegEst:TendEst,:);

VAR_ALL_NAMES=TEXT(1,2:end)

%VARIABLES TO LOG

LOG_V={'CPI','WIP','INDPRO','EURO_INDPRO','HCPI_EURO'};
```

```
logTransform=ismember(VAR_ALL_NAMES,LOG_V);

X(:,logTransform)=log(X(:,logTransform))*100;

%Variables In the Var

N_CCF = (X(:,1));
R_CCF = X(:,2);
CPI = X(:,3);
INDPRO = X(:,4);
WIP = X(:,5);
GFU = X(:,6);
GFC = X(:,7);
FEDFUNDS = X(:,8);
S_FUNDS = X(:,9);
R_CCF_yoy = normalize(X(:,10));
R_CCF_cumsum_noinitial = normalize(X(:,11));
R_CCF_cumsum = normalize(X(:,12));
EURO_INDPRO = X(:,13);
HCPI_EURO = X(:,14);
EURO_RATE = X(:,15);

SHORT_NAME={'GFU','GFC','WIP','R_CCF','INDPRO','CPI','S_FUNDS',...
}
LONG_NAME={'Global Financial Uncertainty','Global Financial Cycle',...
'World Industrial Production','Common Commodity Factor',...
'USA Industrial Production','Consumer Price Index','Federal Funds Rate',...
}

SVAR=[GFU GFC WIP R_CCF_cumsum INDPRO CPI S_FUNDS];
% SVAR
% Choose constant and trend
const_trend = 2;

% Choose number of lags
nbr_lags = 12;

% model
[VAR, VARopt] = VARmodel(SVAR,nbr_lags,const_trend);

% OPTIONS

%Vnames
VARopt.vnames = LONG_NAME;

% number of steps for computation of IRFs and FEVDs
VARopt.nsteps = 48;

% number of bootstrap for sign restriction and else
VARopt.ndraws = 1000;

% size of the shock for IRFs: 0=1stdev, 1=unit shock
VARopt.impact = 0;
```



```
%title on top
VARopt.suptitle = 2;

VARopt.sr_hor = 0;

%frequency
VARopt.frequency = 'm';

% Choose identification model
VARopt.ident = 'short';

% method for computation of recursive stuff ('wold' form MA representation, 'comp' for companion form)
VARopt.recurs = 'wold';

% confidence level for bootstrap, default = 95
VARopt.pctg = 68;

% name of the shocks
VARopt.snames = VARopt.vnames;

%select on variable to plot, if=0 plot all
VARopt.pick = 0;

%printing
[TABLE_VAR, beta] = VARprint(VAR,VARopt);

% bootstrap method
VARopt.method = 'bs';

% IR
[IRF,VAR] = VARir(VAR,VARopt);

% BANDS
[IRF_lower,IRF_upper,IRF_median,IRF_mean] = VARirband(VAR,VARopt);

% Plot impulse response functions
VARirplot_(IRF_mean,VARopt,IRF_lower,IRF_upper);

% VD
% Compute forecast error variance decompositions (VDs) for the VAR model
[VD03, VAR] = VARvd(VAR,VARopt);

% Computing confidence intervals
[vd_INF,vd_SUP,vd_MED,vd_BAR] = VARvdband(VAR,VARopt);

clearvars -except VD03 VD92

%% VD

xPlotLength =16; %cm
yPlotLength =12; %cm
set(gcf,'PaperUnits','centimeters','PaperSize',[xPlotLength yPlotLength]) %[x y]
set(gcf,'PaperPosition',[-1 0 xPlotLength+2 yPlotLength])
```

```
% GFU
figure(1)

a=1
subplot(4,2,a)
plot(1:48,squeeze(VD92(:,1,a)), 'Color', [0.5 0.5 0.5], 'LineWidth',1)
hold on
plot(1:48,squeeze(VD03(:,1,a)), 'b', 'LineWidth',1)
set(gca, 'FontSize',12, 'Fontname', 'Arial');
axis('tight')
title('Global Financial Uncertainty')

a=2
subplot(4,2,a)
plot(1:48,squeeze(VD92(:,1,a)), 'Color', [0.5 0.5 0.5], 'LineWidth',1)
hold on
plot(1:48,squeeze(VD03(:,1,a)), 'b', 'LineWidth',1)
set(gca, 'FontSize',12, 'Fontname', 'Arial');
axis('tight')
title('Global Financial Cycle')

a=3
subplot(4,2,a)
plot(1:48,squeeze(VD92(:,1,a)), 'Color', [0.5 0.5 0.5], 'LineWidth',1)
hold on
plot(1:48,squeeze(VD03(:,1,a)), 'b', 'LineWidth',1)
set(gca, 'FontSize',12, 'Fontname', 'Arial');
axis('tight')
title('World Industrial Production')

a=4
subplot(4,2,a)
plot(1:48,squeeze(VD92(:,1,a)), 'Color', [0.5 0.5 0.5], 'LineWidth',1)
hold on
plot(1:48,squeeze(VD03(:,1,a)), 'b', 'LineWidth',1)
set(gca, 'FontSize',12, 'Fontname', 'Arial');
axis('tight')
title('Common Commodity Factor')

a=5
subplot(4,2,a)
plot(1:48,squeeze(VD92(:,1,a)), 'Color', [0.5 0.5 0.5], 'LineWidth',1)
hold on
plot(1:48,squeeze(VD03(:,1,a)), 'b', 'LineWidth',1)
set(gca, 'FontSize',12, 'Fontname', 'Arial');
axis('tight')
title('USA Industrial Production')

a=6
subplot(4,2,a)
```

```
plot(1:48,squeeze(VD92(:,1,a)), 'Color',[0.5 0.5 0.5], 'LineWidth',1)
hold on
plot(1:48,squeeze(VD03(:,1,a)), 'b', 'LineWidth',1)
set(gca, 'FontSize',12, 'Fontname', 'Arial');
axis('tight')
title('Consumer Price Index')

a=7
subplot(4,2,a)
plot(1:48,squeeze(VD92(:,1,a)), 'Color',[0.5 0.5 0.5], 'LineWidth',1)
hold on
plot(1:48,squeeze(VD03(:,1,a)), 'b', 'LineWidth',1)
%legend('Sample: 1992-2019','Sample: 2003-2019','Location','southeastoutside')
set(gca, 'FontSize',12, 'Fontname', 'Arial');
axis('tight')
title('Federal Funds Rate')

filename=fullfile('C:\Users\Leonardo\Google
Drive\1_UNIPD\16_THESIS\Thesis\Final_results\Results\VD','VD_uncertainty')
savefig(filename);
print(filename, '-djpeg');

% CCF
figure(2)

a=1
subplot(4,2,a)
plot(1:48,squeeze(VD92(:,4,a)), 'Color',[0.5 0.5 0.5], 'LineWidth',1)
hold on
plot(1:48,squeeze(VD03(:,4,a)), 'b', 'LineWidth',1)
set(gca, 'FontSize',12, 'Fontname', 'Arial');
axis('tight')
title('Global Financial Uncertainty')

a=2
subplot(4,2,a)
plot(1:48,squeeze(VD92(:,4,a)), 'Color',[0.5 0.5 0.5], 'LineWidth',1)
hold on
plot(1:48,squeeze(VD03(:,4,a)), 'b', 'LineWidth',1)
set(gca, 'FontSize',12, 'Fontname', 'Arial');
axis('tight')
title('Global Financial Cycle')

a=3
subplot(4,2,a)
plot(1:48,squeeze(VD92(:,4,a)), 'Color',[0.5 0.5 0.5], 'LineWidth',1)
hold on
plot(1:48,squeeze(VD03(:,4,a)), 'b', 'LineWidth',1)
set(gca, 'FontSize',12, 'Fontname', 'Arial');
axis('tight')
title('World Industrial Production')

a=4
```

```
subplot(4,2,a)
plot(1:48,squeeze(VD92(:,4,a)), 'Color',[0.5 0.5 0.5], 'LineWidth',1)
hold on
plot(1:48,squeeze(VD03(:,4,a)), 'b', 'LineWidth',1)
set(gca, 'FontSize',12, 'Fontname', 'Arial');
axis('tight')
title('Common Commodity Factor')

a=5
subplot(4,2,a)
plot(1:48,squeeze(VD92(:,4,a)), 'Color',[0.5 0.5 0.5], 'LineWidth',1)
hold on
plot(1:48,squeeze(VD03(:,4,a)), 'b', 'LineWidth',1)
set(gca, 'FontSize',12, 'Fontname', 'Arial');
axis('tight')
title('USA Industrial Production')

a=6
subplot(4,2,a)
plot(1:48,squeeze(VD92(:,4,a)), 'Color',[0.5 0.5 0.5], 'LineWidth',1)
hold on
plot(1:48,squeeze(VD03(:,4,a)), 'b', 'LineWidth',1)
set(gca, 'FontSize',12, 'Fontname', 'Arial');
axis('tight')
title('Consumer Price Index')

a=7
subplot(4,2,a)
plot(1:48,squeeze(VD92(:,3,a)), 'Color',[0.5 0.5 0.5], 'LineWidth',1)
hold on
plot(1:48,squeeze(VD03(:,3,a)), 'b', 'LineWidth',1)
%legend('Sample: 1992-2019','Sample: 2003-2019','Location','southeastoutside')
set(gca, 'FontSize',12, 'Fontname', 'Arial');
axis('tight')
title('Federal Funds Rate')

filename=fullfile('C:\Users\Leonardo\Google
Drive\1_UNIPD\16_THESIS\Thesis\Final_results\Results\VD', 'VD_CCF')
savefig(filename);
print(filename, '-djpeg');

% Fedfunds
figure(3)

a=1
subplot(4,2,a)
plot(1:48,squeeze(VD92(:,7,a)), 'Color',[0.5 0.5 0.5], 'LineWidth',1)
hold on
plot(1:48,squeeze(VD03(:,7,a)), 'b', 'LineWidth',1)
set(gca, 'FontSize',12, 'Fontname', 'Arial');
axis('tight')
```

```
title('Global Financial Uncertainty')

a=2
subplot(4,2,a)
plot(1:48,squeeze(VD92(:,7,a)), 'Color', [0.5 0.5 0.5], 'LineWidth',1)
hold on
plot(1:48,squeeze(VD03(:,7,a)), 'b', 'LineWidth',1)
set(gca, 'FontSize',12, 'Fontname', 'Arial');
axis('tight')
title('Global Financial Cycle')

a=3
subplot(4,2,a)
plot(1:48,squeeze(VD92(:,7,a)), 'Color', [0.5 0.5 0.5], 'LineWidth',1)
hold on
plot(1:48,squeeze(VD03(:,7,a)), 'b', 'LineWidth',1)
set(gca, 'FontSize',12, 'Fontname', 'Arial');
axis('tight')
title('World Industrial Production')

a=4
subplot(4,2,a)
plot(1:48,squeeze(VD92(:,7,a)), 'Color', [0.5 0.5 0.5], 'LineWidth',1)
hold on
plot(1:48,squeeze(VD03(:,7,a)), 'b', 'LineWidth',1)
set(gca, 'FontSize',12, 'Fontname', 'Arial');
axis('tight')
title('Common Commodity Factor')

a=5
subplot(4,2,a)
plot(1:48,squeeze(VD92(:,7,a)), 'Color', [0.5 0.5 0.5], 'LineWidth',1)
hold on
plot(1:48,squeeze(VD03(:,7,a)), 'b', 'LineWidth',1)
set(gca, 'FontSize',12, 'Fontname', 'Arial');
axis('tight')
title('USA Industrial Production')

a=6
subplot(4,2,a)
plot(1:48,squeeze(VD92(:,7,a)), 'Color', [0.5 0.5 0.5], 'LineWidth',1)
hold on
plot(1:48,squeeze(VD03(:,7,a)), 'b', 'LineWidth',1)
set(gca, 'FontSize',12, 'Fontname', 'Arial');
axis('tight')
title('Consumer Price Index')

a=7
subplot(4,2,a)
plot(1:48,squeeze(VD92(:,7,a)), 'Color', [0.5 0.5 0.5], 'LineWidth',1)
```

```
hold on
plot(1:48,squeeze(VD03(:,7,a)), 'b', 'LineWidth',1)
set(gca, 'FontSize',12, 'Fontname', 'Arial');
axis('tight')
title('Federal Funds Rate')

%legend('Sample: 1992-2019','Sample: 2003-2019','Location','best')

filename=fullfile('C:\Users\Leonardo\Google
Drive\1_UNIPD\16_THESIS\Thesis\Final_results\Results\VD','VD_FF')
savefig(filename);
print(filename, '-djpeg');

% display( [num2str(round(VD03(12,1,3),2)) ' ' num2str(round(VD03(24,1,3),2)) ' '
num2str(round(VD03(36,1,3),2)) ' ' num2str(round(VD03(48,1,3),2))] );
% display( [num2str(round(VD03(12,4,3),2)) ' ' num2str(round(VD03(24,4,3),2)) ' '
num2str(round(VD03(36,4,3),2)) ' ' num2str(round(VD03(48,4,3),2))] );
% display( [num2str(round(VD03(12,7,3),2)) ' ' num2str(round(VD03(24,7,3),2)) ' '
num2str(round(VD03(36,7,3),2)) ' ' num2str(round(VD03(48,7,3),2))] );
```

```

function [VAR, VARopt] = VARmodel(ENDO,nlag,const,EXOG,nlag_ex)
%=====
% Perform vector autoregressive (VAR) estimation with OLS
%=====
% [VAR, VARopt] = VARmodel(ENDO,nlag,const,EXOG,nlag_ex)
% -----
% INPUT
% - ENDO: an (nobs x nvar) matrix of y-vectors
% - nlag: lag length
% -----
% OPTIONAL INPUT
% - const: 0 no constant; 1 constant; 2 constant and trend; 3 constant
%         and trend^2 [dflt = 0]
% - EXOG: optional matrix of variables (nobs x nvar_ex)
% - nlag_ex: number of lags for exogenous variables [dflt = 0]
% -----
% OUTPUT
% - VAR: structure including VAR estimation results
% - VARopt: structure including VAR options (see VARoption)
% -----
% EXAMPLE
% - See VARToolbox_Code.m in "../Primer/"
% =====
% VAR Toolbox 3.0
% Ambrogio Cesa-Bianchi
% ambrogiocesabianchi@gmail.com
% March 2012. Updated November 2020
% -----

%% Check inputs
% -----
[nobs, nvar] = size(ENDO);

% Create VARopt and update it
VARopt = VARoption;
VAR.ENDO = ENDO;
VAR.nlag = nlag;

% Check if there are constant, trend, both, or none
if ~exist('const','var')
    const = 1;
end
VAR.const = const;

% Check if there are exogenous variables
if exist('EXOG','var')
    [nobs2, nvar_ex] = size(EXOG);
    % Check that ENDO and EXOG are conformable
    if (nobs2 ~= nobs)
        error('var: nobs in EXOG-matrix not the same as y-matrix');
    end
    clear nobs2
    % Check if there is lag order of EXOG, otherwise set it to 0

```

```

    if ~exist('nlag_ex','var')
        nlag_ex = 0;
    end
    VAR.EXOG = EXOG;
else
    nvar_ex = 0;
    nlag_ex = 0;
    VAR.EXOG = [];
end

%% Save some parameters and create data matrices
% -----
nobs       = nobs - max(nlag,nlag_ex);
VAR.nobs   = nobs;
VAR.nvar   = nvar;
VAR.nvar_ex = nvar_ex;
VAR.nlag   = nlag;
VAR.nlag_ex = nlag_ex;
ncoeff     = nvar*nlag;
VAR.ncoeff = ncoeff;
ncoeff_ex  = nvar_ex*(nlag_ex+1);
ntotcoeff  = ncoeff + ncoeff_ex + const;
VAR.ntotcoeff = ntotcoeff;
VAR.const  = const;

% Create independent vector and lagged dependent matrix
[Y, X] = VARmakexy(ENDO,nlag,const);

% Create (lagged) exogenous matrix
if nvar_ex>0
    X_EX = VARmakelags(EXOG,nlag_ex);
    if nlag == nlag_ex
        X = [X X_EX];
    elseif nlag > nlag_ex
        diff = nlag - nlag_ex;
        X_EX = X_EX(diff+1:end,:);
        X = [X X_EX];
    elseif nlag < nlag_ex
        diff = nlag_ex - nlag;
        Y = Y(diff+1:end,:);
        X = [X(diff+1:end,:) X_EX];
    end
end

%% OLS estimation equation by equation
% -----
for j=1:nvar
    Yvec = Y(:,j);
    OLSout = OLSmodel(Yvec,X,0);
    aux = ['eq' num2str(j)];
    eval( ['VAR.' aux '.beta = OLSout.beta;'] ); % bhats
    eval( ['VAR.' aux '.tstat = OLSout.tstat;'] ); % t-stats
end

```



```

eval( ['VAR.' aux '.bstd = OLSout.bstd;'] ); % beta std error
% compute t-probs
tstat = zeros(ncoeff,1);
tstat = OLSout.tstat;
tout = tdis_prb(tstat,nobse-ncoeff);
eval( ['VAR.' aux '.tprob = tout;'] ); % t-probs
eval( ['VAR.' aux '.resid = OLSout.resid;'] );% resid
eval( ['VAR.' aux '.yhat = OLSout.yhat;'] ); % yhats
eval( ['VAR.' aux '.y = Yvec;'] ); % actual y
eval( ['VAR.' aux '.rsqr = OLSout.rsqr;'] ); % r-squared
eval( ['VAR.' aux '.rbar = OLSout.rbar;'] ); % r-adjusted
eval( ['VAR.' aux '.sige = OLSout.sige;'] ); % standard error
eval( ['VAR.' aux '.dw = OLSout.dw;'] ); % DW
end

%% Compute the matrix of coefficients & VCV
% -----
Ft = (X'*X)\(X'*Y);
VAR.Ft = Ft;
F = Ft';
VAR.F = Ft';
SIGMA = (1/(nobse-ntotcoeff))*(Y-X*Ft)'*(Y-X*Ft); % adjusted for # of estimated ✓
coeff per equation
VAR.sigma = SIGMA;
VAR.resid = Y - X*Ft;
VAR.X = X;
VAR.Y = Y;
if nvar_ex > 0
    VAR.X_EX = X_EX;
end

%% Companion matrix of F and max eigenvalue
% -----
Fcomp = [F(:,1+const:nvar*nlag+const); eye(nvar*(nlag-1)) zeros(nvar*(nlag-1), ✓
nvar)];
VAR.Fcomp = Fcomp;
VAR.maxEig = max(abs(eig(Fcomp)));

%% Initialize other results
% -----
VAR.B = []; % structural impact matrix (need identification: see VARir/VARfevd)
VAR.b = []; % first columns of structural impact matrix (need identification: ✓
see VARir/VARfevd)
VAR.PSI = []; % Wold multipliers (computed only with VARir/VARfevd)
VAR.Fp = []; % Recursive F by lag (useful to compute MA representation)
VAR.IV = []; % External instruments for identification

```

```

function [IR, VAR] = VARir(VAR,VARopt)
% =====
% Compute impulse responses (IRs) for a VAR model estimated with the
% VARmodel.m function. Four identification schemes can be specified:
% zero contemporaneous restrictions, zero long-run restrictions, sign
% restrictions, and external instrumenmts.
% =====
% [IRF, VAR] = VARir(VAR,VARopt)
% -----
% INPUT
%   - VAR: structure, result of VARmodel.m
%   - VARopt: options of the VAR (result of VARmodel.m)
% -----
% OUTPUT
%   - IR(:, :, :) : matrix with IRF (H horizons, N variables, N shocks)
%   - VAR: structure including VAR estimation results. Note here that the
%         structure VAR is an output of VARmodel tpp. This fucntion adds to
%         VAR some additional results, e.g. VAR.B is the structural impact
%         matrix
% =====
% VAR Toolbox 3.0
% Ambrogio Cesa-Bianchi
% ambrogiocesabianchi@gmail.com
% March 2012. Updated November 2020
% -----

%% Check inputs
%=====
if ~exist('VAR','var')
    error('You need to provide VAR structure, result of VARmodel');
end
IV = VAR.IV;
if strcmp(VARopt.ident,'iv')
    if isempty(IV)
        error('You need to provide the data for the instrument in VAR (IV)');
    end
end

%% Retrieve and initialize variables
%=====
nsteps = VARopt.nsteps;
impact = VARopt.impact;
shut    = VARopt.shut;
recurs  = VARopt.recurs;
Fcomp  = VAR.Fcomp;
nvar    = VAR.nvar;
nlag    = VAR.nlag;
sigma   = VAR.sigma;
IR      = nan(nsteps,nvar,nvar);

%% Compute Wold representation

```

```

%=====
% Initialize Wold multipliers
PSI = zeros(nvar,nvar,nsteps);
% Re-write F matrix to compute multipliers
VAR.Fp = zeros(nvar,nvar,nlag);
I = VAR.const+1;
for ii=1:nsteps
    if ii<=nlag
        VAR.Fp(:, :, ii) = VAR.F(:, I:I+nvar-1);
    else
        VAR.Fp(:, :, ii) = zeros(nvar,nvar);
    end
    I = I + nvar;
end
% Compute multipliers
PSI(:, :, 1) = eye(nvar);
for ii=2:nsteps
    jj=1;
    aux = 0;
    while jj<ii
        aux = aux + PSI(:, :, ii-jj)*VAR.Fp(:, :, jj);
        jj=jj+1;
    end
    PSI(:, :, ii) = aux;
end
% Update VAR with Wold multipliers
VAR.PSI = PSI;

%% Identification: Recover B matrix
%=====
% B matrix is recovered with Cholesky decomposition
if strcmp(VARopt.ident, 'short')
    [out, chol_flag] = chol(sigma);
    if chol_flag~=0; error('VCV is not positive definite'); end
    B = out';
% B matrix is recovered with Cholesky on cumulative IR to infinity
elseif strcmp(VARopt.ident, 'long')
    Finf_big = inv(eye(length(Fcomp))-Fcomp); % from the companion
    Finf = Finf_big(1:nvar,1:nvar);
    D = chol(Finf*sigma*Finf)'; % identification: u2 has no effect on y1 in the
long run
    B = Finf\D;
% B matrix is recovered with SR.m
elseif strcmp(VARopt.ident, 'sign')
    if isempty(VAR.B)
        error('You need to provide the B matrix with SR.m and/or SignRestrictions.
m')
    else
        B = VAR.B;
    end
% B matrix is recovered with external instrument IV
elseif strcmp(VARopt.ident, 'iv')
    % Recover residuals (first variable is the one to be instrumented - order

```

```

matters!)
    up = VAR.resid(:,1);      % residuals to be instrumented
    uq = VAR.resid(:,2:end); % residulas for second stage

    % Make sample of IV comparable with up and uq
    [aux, fo, lo] = CommonSample([up IV(VAR.nlag+1:end,:)]);
    p = aux(:,1);
    q = uq(end-length(p)+1:end,:); pq = [p q];
    Z = aux(:,2:end);

    % Run first stage regression and fitted
    FirstStage = OLSmodel(p,Z);
    p_hat = FirstStage.yhat;

    % Recover first column of B matrix with second stage regressions
    b(1,1) = 1; % Start with impact IR normalized to 1
    sqsp = zeros(size(q,2),1);
    for ii=2:nvar
        SecondStage = OLSmodel(q(:,ii-1),p_hat);
        b(ii,1) = SecondStage.beta(2);
        sqsp(ii-1) = SecondStage.beta(2);
    end
    % Update size of the shock (ftn 4 of Gertler and Karadi (2015))
    sigma_b = (1/(length(pq)-VAR.ntotcoeff))*...
        (pq-repmat(mean(pq),size(pq,1),1))'*...
        (pq-repmat(mean(pq),size(pq,1),1));
    s21s11 = sqsp;
    S11 = sigma_b(1,1);
    S21 = sigma_b(2:end,1);
    S22 = sigma_b(2:end,2:end);
    Q = s21s11*S11*s21s11'-(S21*s21s11'+s21s11*S21')+S22;
    sp = sqrt(S11-(S21-s21s11*S11)'*(Q\ (S21-s21s11*S11)));
    % Rescale b vector
    b = b*sp;
    B = zeros(nvar,nvar);
    B(:,1) = b;
% If none of the above, you've done somerthing wrong :)
else
    disp('-----')
    disp('Identification incorrectly specified.')
    disp('Choose one of the following options:');
    disp('- short: zero contemporaneous restrictions');
    disp('- long: zero long-run restrictions');
    disp('- sign: sign restrictions');
    disp('- iv: external instrument');
    disp('-----')
    error('ERROR. See details above');
end

%% Compute the impulse response
%=====
for mm=1:nvar
    % Set to zero a row of the companion matrix if "shut" is selected

```

```
if shut~=0
    Fcomp(shut,:) = 0;
end
% Initialize the impulse response vector
response = zeros(nvar, nsteps);
% Create the impulse vector
impulse = zeros(nvar,1);
% Set the size of the shock
if impact==0
    impulse(mm,1) = 1; % one stdev shock
elseif impact==1
    impulse(mm,1) = 1/B(mm,mm); % unitary shock
else
    error('Impact must be either 0 or 1');
end
% First period impulse response (=impulse vector)
response(:,1) = B*impulse;
% Shut down the response if "shut" is selected
if shut~=0
    response(shut,1) = 0;
end
% Recursive computation of impulse response
if strcmp(recurs,'wold')
    for kk = 2:nsteps
        response(:,kk) = PSI(:, :, kk)*B*impulse;
    end
elseif strcmp(recurs,'comp')
    for kk = 2:nsteps
        FcompN = Fcomp^(kk-1);
        response(:,kk) = FcompN(1:nvar,1:nvar)*B*impulse;
    end
end
IR(:, :, mm) = response';
end
% Update VAR with structural impact matrix
VAR.B = B;
if strcmp(VARopt.ident,'iv')
    VAR.FirstStage = FirstStage;
    VAR.sigma_b = sigma_b;
    VAR.b = b;
end
```

```

function [INF,SUP,MED,BAR] = VARirband(VAR,VARopt)
% =====
% Calculate confidence intervals for impulse response functions computed
% with VARir
% =====
% [INF,SUP,MED,BAR] = VARirband(VAR,VARopt)
% -----
% INPUTS
% - VAR: structure, result of VARmodel.m
% - VARopt: options of the VAR (result of VARmodel.m)
% -----
% OUTPUT
% - INF(:,:,,:): lower confidence band (H horizons, N variables, N shocks)
% - SUP(:,:,,:): upper confidence band (H horizons, N variables, N shocks)
% - MED(:,:,,:): median response (H horizons, N variables, N shocks)
% - BAR(:,:,,:): mean response (H horizons, N variables, N shocks)
% -----
% EXAMPLE
% - See VARToolbox_Code.m in "../Primer/"
% =====
% VAR Toolbox 3.0
% Ambrogio Cesa-Bianchi
% ambrogiocesabianchi@gmail.com
% March 2012. Updated November 2020
% -----

%% Check inputs
%-----
if ~exist('VAR','var')
    error('You need to provide VAR structure, result of VARmodel');
end
if ~exist('VARopt','var')
    error('You need to provide VAR options (VARopt from VARmodel)');
end

%% Retrieve and initialize variables
%-----
nsteps = VARopt.nsteps;
ndraws = VARopt.ndraws;
pctg = VARopt.pctg;
method = VARopt.method;

Ft = VAR.Ft; % this is \Phi' in the notes (rows are coeffs, columns are eqs)
nvar = VAR.nvar;
nvar_ex = VAR.nvar_ex;
nlag = VAR.nlag;
nlag_ex = VAR.nlag_ex;
const = VAR.const;
nobs = VAR.nobs;
resid = VAR.resid;
ENDO = VAR.ENDO;
EXOG = VAR.EXOG;

```

```

IV      = VAR.IV;

INF = zeros(nsteps,nvar,nvar);
SUP = zeros(nsteps,nvar,nvar);
MED = zeros(nsteps,nvar,nvar);
BAR = zeros(nsteps,nvar,nvar);

%% Create the matrices for the loop
%-----
y_artificial = zeros(nobs+nlag,nvar);

%% Loop over the number of draws
%-----
tt = 1; % numbers of accepted draws
ww = 1; % index for printing on screen
while tt<=ndraws

    % Display number of loops
    if tt==VARopt.mult*ww
        disp(['Loop ' num2str(tt) ' / ' num2str(ndraws) ' draws'])
        ww=ww+1;
    end

%% STEP 1: choose the method and generate the residuals
    if strcmp(method,'bs')
        % Use the residuals to bootstrap: generate a random number bounded
        % between 0 and # of residuals, then use the ceil function to select
        % that row of the residuals (this is equivalent to sampling with
replacement)
        u = resid(ceil(size(resid,1)*rand(nobs,1)),:);
    elseif strcmp(method,'wild')
        % Wild bootstrap based on simple distribution (~Rademacher)
        if strcmp(VARopt.ident,'iv')
            rr = 1-2*(rand(nobs,size(IV,2))>0.5);
            u = resid.*(rr*ones(size(IV,2),nvar));
            Z = [IV(1:nlag,:); IV(nlag+1:end,:).*rr];
        else
            rr = 1-2*(rand(nobs,1)>0.5);
            u = resid.*(rr*ones(1,nvar));
        end
    else
        error(['The method ' method ' is not available'])
    end

%% STEP 2: generate the artificial data

%% STEP 2.1: initial values for the artificial data
% Intialize the first nlag observations with real data
LAG=[];
for jj = 1:nlag
    y_artificial(jj,:) = ENDO(jj,:);
    LAG = [y_artificial(jj,:) LAG];
end

```

```

% Initialize the artificial series and the LAGplus vector
T = [1:nobs]';
if const==0
    LAGplus = LAG;
elseif const==1
    LAGplus = [1 LAG];
elseif const==2
    LAGplus = [1 T(1) LAG];
elseif const==3
    T = [1:nobs]';
    LAGplus = [1 T(1) T(1).^2 LAG];
end
if nvar_ex~=0
    LAGplus = [LAGplus VAR.X_EX(jj-nlag+1,:)];
end

%% STEP 2.2: generate artificial series
% From observation nlag+1 to nobs, compute the artificial data
for jj = nlag+1:nobs+nlag
    for mm = 1:nvar
        % Compute the value for time=jj
        y_artificial(jj,mm) = LAGplus * Ft(1:end,mm) + u(jj-nlag,mm);
    end
    % now update the LAG matrix
    if jj<nobs+nlag
        LAG = [y_artificial(jj,:) LAG(1,1:(nlag-1)*nvar)];
        if const==0
            LAGplus = LAG;
        elseif const==1
            LAGplus = [1 LAG];
        elseif const==2
            LAGplus = [1 T(jj-nlag+1) LAG];
        elseif const==3
            LAGplus = [1 T(jj-nlag+1) T(jj-nlag+1).^2 LAG];
        end
        if nvar_ex~=0
            LAGplus = [LAGplus VAR.X_EX(jj-nlag+1,:)];
        end
    end
end

%% STEP 3: estimate VAR on artificial data.
if nvar_ex~=0
    [VAR_draw, ~] = VARmodel(y_artificial,nlag,const,EXOG,nlag_ex);
else
    [VAR_draw, ~] = VARmodel(y_artificial,nlag,const);
end
% If "iv" identification is selected, update VAR_draw with bootstrapped
%instrument
if exist('Z','var')
    VAR_draw.IV = Z;
end

%% STEP 4: calculate "ndraws" impulse responses and store them

```



```
% Uses options from VARopt and parameters from VAR_draw (from step 3)
% to compute IRFs
[IR_draw, VAR_draw] = VARir(VAR_draw,VARopt);
if VAR_draw.maxEig<.9999
    IR(:, :, :, tt) = IR_draw;
    tt=tt+1;
end
end
disp('-- Done!');
disp(' ');

%% Compute the error bands
%-----
pctg_inf = (100-pctg)/2;
pctg_sup = 100 - (100-pctg)/2;
INF(:, :, :) = prctile(IR(:, :, :, :),pctg_inf,4);
SUP(:, :, :) = prctile(IR(:, :, :, :),pctg_sup,4);
MED(:, :, :) = prctile(IR(:, :, :, :),50,4);
BAR(:, :, :) = mean(IR(:, :, :, :),4);
```

```

function [VD, VAR] = VARvd(VAR,VARopt)
% =====
% Compute forecast error variance decompositions (VDs) for a VAR model
% estimated with the VARmodel.m function. Three identification schemes can
% be specified: zero contemporaneous restrictions, zero long-run
% restrictions, and sign restrictions
% =====
% [VD, VAR] = VARvd(VAR,VARopt)
% -----
% INPUT
%   - VAR: structure, result of VARmodel.m
%   - VARopt: options of the VAR (result of VARmodel.m)
% -----
% OUTPUT
%   - VD(:, :, :): matrix with FEVDs (H horizons, N shocks, N variables)
%   - VAR: structure including VAR estimation results
%       * VAR.B: structural impact matrix
% -----
% EXAMPLE
%   - See VARToolbox_Code.m in "../Primer/"
% =====
% VAR Toolbox 3.0
% Ambrogio Cesa-Bianchi
% ambrogiocesabianchi@gmail.com
% March 2012. Updated November 2020
% -----
%% Check inputs
%=====
if ~exist('VAR','var')
    error('You need to provide VAR structure, result of VARmodel');
end
IV = VAR.IV;
if strcmp(VARopt.ident,'iv')
    disp('-----')
    disp('Forecast error variance decomposition not available with')
    disp('external instruments identification (iv)');
    disp('-----')
    error('ERROR. See details above');
end

%% Retrieve and initialize variables
%=====
nsteps = VARopt.nsteps;
ident   = VARopt.ident;
Fcomp   = VAR.Fcomp;
nlag    = VAR.nlag;
nvar    = VAR.nvar;
sigma   = VAR.sigma;
VD      = zeros(nsteps,nvar,nvar);
SE      = zeros(nsteps,nvar);
MSE     = zeros(nvar,nvar,nsteps);
MSE_shock = zeros(nvar,nvar,nsteps);

```

```

%% Compute Wold representation
%=====
% Initialize Wold multipliers
PSI = zeros(nvar,nvar,nsteps);
% Re-write F matrix to compute multipliers
VAR.Fp = zeros(nvar,nvar,nlag);
I = VAR.const+1;
for kk=1:nsteps
    if kk<=nlag
        VAR.Fp(:, :,kk) = VAR.F(:, I:I+nvar-1);
    else
        VAR.Fp(:, :,kk) = zeros(nvar,nvar);
    end
    I = I + nvar;
end
% Compute multipliers
PSI(:, :,1) = eye(nvar);
for kk=2:nsteps
    jj=1;
    aux = 0;
    while jj<kk
        aux = aux + PSI(:, :,kk-jj)*VAR.Fp(:, :,jj);
        jj=jj+1;
    end
    PSI(:, :,kk) = aux;
end
% Update VAR with Wold multipliers
VAR.PSI = PSI;

%% Identification: Recover B matrix
%=====
% B matrix is recovered with Cholesky decomposition
if strcmp(ident,'short')
    [out, chol_flag] = chol(sigma);
    if chol_flag~=0; error('\VCV is not positive definite'); end
    B = out';
% B matrix is recovered with Cholesky on cumulative IR to infinity
elseif strcmp(ident,'long')
    Finf_big = inv(eye(length(Fcomp))-Fcomp); % from the companion
    Finf = Finf_big(1:nvar,1:nvar);
    D = chol(Finf*sigma*Finf)'; % identification: u2 has no effect on y1 in the
long run
    B = Finf\D;
% B matrix is recovered with SR.m
elseif strcmp(ident,'sign')
    if isempty(VAR.B)
        error('You need to provide the B matrix with SR.m and/or SignRestrictions.
m')
    else
        B = VAR.B;
    end
% B matrix is recovered with external instrument IV
elseif strcmp(ident,'iv')

```

```

disp('-----')
disp('Forecast error variance decomposition not available yet ')
disp('with external instruments identification (iv)');
disp('-----')
error('ERROR. See details above');
% If none of the above, you've done somerthing wrong :)
else
disp('-----')
disp('Identification incorrectly specified.')
disp('Choose one of the following options:');
disp('- short: zero contemporaneous restrictions');
disp('- long: zero long-run restrictions');
disp('- sign: sign restrictions');
disp('- iv: external instrument');
disp('-----')
error('ERROR. See details above');
end
%% Calculate the contribution to the MSE for each shock (i.e, VD)
%=====
for ii = 1:nvar % loop for the shocks

% The 1-step ahead variance of the forecast error is the variance of
% the residulas (sigma).
MSE(:, :, 1) = sigma;
for nn = 2:nsteps
MSE(:, :, nn) = MSE(:, :, nn-1) + PSI(:, :, nn)*sigma*PSI(:, :, nn)';
end
% The 1-step ahead variance of the mm^th structural forecast error is
% the square of the mm^th column of the structural impact matrix (B)
MSE_shock(:, :, 1) = B(:, ii)*B(:, ii)';
for nn = 2:nsteps
MSE_shock(:, :, nn) = MSE_shock(:, :, nn-1) + PSI(:, :, nn)*MSE_shock(:, :, 1)*PSI
(:, :, nn)';
end

% Compute the Forecast Error Covariance Decomposition
FECD = MSE_shock(1:nvar, 1:nvar, :)./MSE(1:nvar, 1:nvar, :);

% Select only the variance terms
for nn = 1:nsteps
for kk = 1:nvar
VD(nn, ii, kk) = 100*FECD(kk, kk, nn);
SE(nn, :) = sqrt(diag(MSE(1:nvar, 1:nvar, nn))' );
end
end
end

% Update VAR with structural impact matrix
VAR.B = B;

```

```

%% modified by me
function VARirplot_(IR,VARopt,INF,SUP)
% =====
% Plot the IRs computed with VARir
% =====
% VARirplot(IR,VARopt,vnames,INF,SUP)
% -----
% INPUT
%   - IR(:, :, :) : matrix with IRF (H horizons, N variables, N shocks)
%   - VARopt: options of the VAR (see VARopt from VARmodel)
% -----
% OPTIONAL INPUT
%   - INF: lower error band
%   - SUP: upper error band
% -----
% EXAMPLE
%   - See VARToolbox_Code.m in "../Primer/"
% =====
% VAR Toolbox 3.0
% Ambrogio Cesa-Bianchi
% ambrogiocesabianchi@gmail.com
% March 2012. Updated April 2021
% -----

%% Check inputs
%=====
if ~exist('VARopt','var')
    error('You need to provide VAR options (VARopt from VARmodel)');
end
% If there is VARopt get the vnames
vnames = VARopt.vnames;
% Check they are not empty
if isempty(vnames)
    error('You need to add label for endogenous variables in VARopt');
end
% Define shock names
if isempty(VARopt.snames)
    snames = VARopt.vnames;
else
    snames = VARopt.snames;
end

%% Retrieve and initialize variables
%=====
filename = [VARopt.figname 'IR_'];
quality = VARopt.quality;
suptitle = VARopt.suptitle;
pick = VARopt.pick;

% Initialize IR matrix
[nsteps, nvars, nshocks] = size(IR);

```

```

% If one shock is chosen, set the right value for nshocks
if pick<0 || pick>nvars
    error('The selected shock is non valid')
else
    if pick==0
        pick=1;
    else
        nshocks = pick;
    end
end

% Define the rows and columns for the subplots
row = ceil(nvars/2);
col = 2;

% Define a timeline
steps = 1:1:nsteps;
x_axis = zeros(1,nsteps);

%% Plot
=====
SwatheOpt = PlotSwatheOption;
%SwatheOpt.marker = '*';
SwatheOpt.trans = 1;

% Change default axes fonts.
set(0,'DefaultAxesFontName', 'Courier New')
set(0,'DefaultAxesFontWeight','normal')
set(0,'DefaultAxesFontSize', 8)
set(0,'defaultAxesXColor',[.3 .3 .3])
set(0,'defaultAxesYColor',[.3 .3 .3])

% Change default text fonts.
set(0,'DefaultTextFontName', 'Courier New')
set(0,'DefaultTextFontSize', 11)
set(0,'DefaultTextColor',[.3 .3 .3])

SwatheOpt.swathecol = [.9 .9 .9]; % color(6,:);
SwatheOpt.linecol = [1. .4 .0]; % color(1,:);
SwatheOpt.frequency = 'm';
%
Mcolor = [0 50 100]/255;
Ocolor = [255 0 0]/255;

FigSize(VARopt.FigSize(1),VARopt.FigSize(2))
for jj=pick:nshocks
    for ii=1:nvars
        subplot(row,col,ii);
        plot(steps,IR(:,ii,jj),'-', 'LineWidth',1.2, 'MarkerSize',2.5, 'color',Mcolor, 'MarkerEdgeColor',Mcolor); hold on
        if exist('INF','var') && exist('SUP','var')
            PlotSwathe(IR(:,ii,jj),[INF(:,ii,jj) SUP(:,ii,jj)],SwatheOpt); hold on;
        end
    end
end

```

```
axis tight; grid on;
plot(x_axis, '-k', 'LineWidth', 0.2); hold on
xlim([1 nsteps]);
set(gca, 'XTick', [0;6;12;18;24;30;36;42;48])
%   set(gca, 'XTickLabel', ['0 ','6','12','18','24','30','36','48'])
title([snames{ii}], 'FontWeight', 'bold', 'FontSize', 10);
set(gca, 'Layer', 'top');
end
% Save
FigName = [filename snames{jj}];

if quality
    if suptitle==1
        Alphabet = char('a'+(1:nshocks)-1);
        SupTitle([Alphabet{jj} ' ) IR to a shock to ' vnames{jj}])
    end
    set(gcf, 'Color', 'w');
    export_fig(FigName, '-pdf', '-painters')
else
    xPlotLength = 16; %cm
    yPlotLength = 12; %cm
    set(gcf, 'PaperUnits', 'centimeters', 'PaperSize', [xPlotLength yPlotLength]) %↙
[x y]
    set(gcf, 'PaperPosition', [-1 0 xPlotLength+2 yPlotLength])
    %[left bottom width height]
    print(gcf, '-djpeg', FigName);
end
clf('reset');
end

close all
```